The Parental Wage Gap and the Development of Socio-emotional Skills in Children

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Abstract

In this paper, I study the causal impact of the parental wage gap (PWG)—defined as the relative potential wages of mothers and fathers—on children's socio-emotional skills. I leverage administrative and survey data from Germany to create exogenous between-sibling variation in the PWG through a shift-share design. I find that decreases in the PWG do not affect children's socio-emotional skills as measured by their personality traits, externalizing/internalizing behaviors, BMI, and school progression. This null effect can be rationalized by the offsetting effects of the PWG on monetary and time investments of parents.

JEL-Codes: J13; J16; J22; J24
Keywords: Gender gaps; skill development; parental investments

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1 INTRODUCTION

Children's skill development crucially depends on the money and time resources provided by parents. The provision of these resources is the outcome of a decision process in which mothers and fathers balance the well-being of their children against alternative uses of their money and time. How parents solve this trade-off depends on mothers' and fathers' labor market incentives. For example, standard models of household decision-making predict that spouses with a comparative advantage in market work will spend less time at home with the children than their partner (Becker, 1981). In many countries, parent's relative incentives have changed profoundly in recent decades (Blau and Kahn, 2017; Olivetti and Petrongolo, 2016). For example, the average gender pay gap in OECD countries has almost halved from 19.0% in 1995 to 11.2% in 2020 (OECD, 2023). This trend is likely to have significant consequences for parental resource allocations and the environments in which children grow up. How do these changes affect children's development? While the "grand gender convergence" in labor markets is well-documented and the closure of remaining gaps remains high on the policy agenda (Cortés and Pan, 2023; Gender Policy Council, 2021; Goldin, 2014), causal evidence linking the pay gaps of mothers and fathers to the skill formation of their children is scant.

In this paper, I study how changes in the parental wage gap (PWG)—defined as the relative potential wages of mothers and fathers—affect the skill formation of their children. In particular, I focus on the development of socio-emotional skills. Socio-emotional (or non-cognitive) skills encompass various concepts such as emotional intelligence, locus of control, personality traits (e.g., conscientiousness), and preferences (e.g., patience).[1] Economic research has increasingly focused on these skills as they are highly predictive of important life outcomes, including health (Almlund et al., 2011; Savelyev, 2022), education (Almås et al., 2016; Papageorge et al., 2019), family formation (Dupuy and Galichon, 2014; Serra-Garcia, 2021), and earnings (Cubel et al., 2016; Deming, 2017). Notably, the predictive power of socio-emotional skills emerges during childhood, suggesting that changes to these skills early in life may have lasting consequences in the long-run (Attanasio et al., 2020b; Sorrenti et al., forthcoming).

[1] In economics, they are often considered a residual dimension of skills not captured by standardized tests (Humphries and Kosse, 2017).

I leverage a combination of survey and administrative data from Germany to analyze the link between the PWG and children's socio-emotional skills. Germany is an interesting setting in which to study the effect of the PWG on child development. On the one hand, the institutional context broadly represents other industrialized countries in Europe and the OECD. On the other hand, the country is characterized by substantial regional heterogeneity in gender gaps, a legacy of the 41-year division into the communist East and the capitalist West (Boelmann et al., forthcoming; Lippmann et al., 2020). Specifically, I use the 2005–2019 waves of the German Socio-economic Panel (GSOEP) to construct a sample of $5,484$ siblings aged 2–10 for whom I observe measures of socio-emotional skills and parental investments at the same age but in different calendar years. Furthermore, I use administrative wage data from the Federal Employment Agency of Germany and working time data from the German Microcensus to construct measures of potential hourly wages for mothers and fathers. The combination of these different data sources allows the analysis of within-family changes in children's socio-emotional skills and parental investments as a function of changes in the PWG.

There are two main challenges to identifying the causal effect of the PWG on children's development. First, there are unobserved joint determinants of parental wages and child outcomes. For example, consider two families with different preferences for whether the mother should stay home with their preschool children. Since both parental wages and the socio-emotional skills of children are affected by different childcare arrangements during this age period (e.g., Baker et al., 2019; Houmark et al., 2022), a comparison across families would be confounded by omitted variable bias. I address such concerns by implementing a within-family comparison that rules out any confounding effects through time-constant factors specific to families when their children are of a particular age.

Second, a within-family comparison may still reflect PWGs resulting from parents' endogenous labor supply responses. For example, consider a father who responds to the behavioral problems of his child by switching to a less time-consuming but lower-paying job. In such cases, the effect of intra-family changes in the PWG on children's socio-emotional skills would be confounded by reverse causality. To address this concern, I use a shift-share design to replace actual wages with potential wages (Goldsmith-Pinkham et al., 2020). These potential wages are weighted averages of wages paid in different sectors of the economy ("shift"), where weights are given by the historic employment exposure of specific groups to these sectors ("share"). This measure of the PWG reflects demand-driven temporal variation in labor market incentives for mothers and fathers that is plausibly exogenous to the labor supply decisions of individual parents.

Thus, the identification strategy combines a within-family sibling comparison with a shift-share design to measure parental wages. I validate the underlying identification assumptions as follows. First, the measures of potential wages must be orthogonal to intra-family variation in child characteristics. Therefore, I show that within-family differences in potential wages are uncorrelated with a large set of child characteristics that predict their socio-emotional skills and parental investments. Second, the estimates would be susceptible to violations in the identification assumption if the identifying variation originated from a few economic sectors. Therefore, I show that the Rotemberg weights associated with maternal and paternal potential wages are widely dispersed across different sectors of the economy (Goldsmith-Pinkham et al., 2020). Lastly, potential wages must be good proxies for mothers' and fathers' actual labor market incentives. Therefore, I show that within-person changes in potential wages are highly predictive of within-person changes in actual wages of mothers and fathers.

The results of the analysis are threefold. First, I show that both mothers and fathers respond to increases in their potential wages by increasing their working time: a 10% increase in the potential wages of mothers (fathers) increases their working time by 1.2 (0.5) hours per day. For both mothers and fathers, these increases are mostly accounted for by reductions in personal time for hobbies and education. The time they devote to childcare remains unaffected. Furthermore, mothers and fathers react asymmetrically to changes in the potential wages of their partners. Fathers are unresponsive to the wage changes of mothers. Mothers, however, substitute market work with childcare if the wages of their partners increase: a 10% increase in the potential wages of fathers decreases (increases) the mother's working time (childcare time) by 0.5 hours per day. These results confirm that decreases in the PWG, either through increases in maternal wages or decreases in paternal wages, have significant consequences for parental time allocations and the environments in which children grow up.

Second, I find that these changes in childhood environments do not affect the socio-emotional skill development of children. In particular, I show that a 10% decrease in the PWG would not affect children's openness, conscientiousness, agreeableness, neuroticism, externalizing, and internalizing behavior. A statistically significant effect only emerges for extraversion, i.e., for one out of the seven considered measures of children's socio-emotional skills. However, this result is not stable across robustness analyses, and its statistical significance vanishes once I correct standard errors for multiple hypothesis testing. Are these null results meaningful? To assess the economic magnitude of these findings, I translate the changes in socio-emotional skills into the implied earnings effects at age 50. Considering the 95% confidence intervals as credible effect regions, I can exclude earnings increases/decreases that are larger than 1% per year for six out of seven considered dimensions of children's socio-emotional skills. Furthermore, I compare these implied magnitudes against those from other interventions in the existing literature. This comparison shows that the effects of a 10% decrease in the PWG are small compared to other interventions and that I can exclude the majority of established effect sizes from the credible effect regions of my estimates.

Third, I show that these null effects may be explained by the opposing forces that changing PWGs exert on the money and time investments of parents. On the one hand, a 10% decrease in the PWG increases the probability of using informal childcare by 0.09 points. Since informal childcare is often inferior to maternal childcare at home, this change will likely negatively affect children's socio-emotional skills (Bernal and Keane, 2011; Datta Gupta and Simonsen, 2010; Duncan et al., 2023). On the other hand, a 10% decrease in the PWG increases disposable household income by 2.18 Thsd. € per year and increases the total share of resources controlled by mothers by 6.58 percentage points. Since money is an important input into child development and mothers have a higher propensity to spend their money on their children, these changes are likely to exert a positive effect on children's socio-emotional skills (Agostinelli and Sorrenti, 2018; Akee et al., 2018; Dahl and Lochner, 2012; Duflo, 2012; Løken et al., 2012; Lundberg et al., 1997; Nicoletti et al., 2023). I furthermore support the explanation of offsetting parental investments in heterogeneity analyses. While the general evidence for heterogeneous treatment effects is limited, I show that decreases in the PWG can lead to detrimental effects on children if the increased exposure to informal care is not compensated by increases in household income or the maternal income share. For example, compared to parents in East Germany, parents in West Germany react to decreasing PWGs with a higher likelihood of using informal childcare. At the same time, this increased exposure to informal care is not offset by corresponding increases in household income or the maternal income share, leading to higher behavioral problems in response to the PWG among children in West Germany.

These results are robust to various sensitivity checks, including alternative constructions of potential wages, alternative sample restrictions, and additional control variables to account for differences in sibling characteristics and differential time trends by labor market regions and education groups. Furthermore, I show that the identifying variation is orthogonal to the recent expansion of public childcare in Germany (Felfe and Lalive, 2018). I also replicate the main findings using a first-difference estimator that uses within-child variation over time instead of within-family variation across siblings (Agostinelli and Sorrenti, 2018; Dahl and Lochner, 2012). Moreover, I show that these null effects persist in the long run and that other child outcomes like BMI, delayed school entry, and school tracking remain unaffected.

This study contributes to three strands of the literature. First, I contribute to the literature on socio-emotional skills. Next to cognitive skills and health, socio-emotional skills are a dimension of human capital that matters for various important life outcomes. Therefore, social scientists have increased their attention on the causal factors underlying the formation of these skills. These factors include genetic endowments (Demange et al., 2021), home environments (Carneiro et al., 2013; García-Miralles and Gensowski, forthcoming), monetary resources (Akee et al., 2018), parental time investments (Fiorini and Keane, 2014; Houmark et al., 2022), parenting styles (Deckers et al., 2021), the quality of schools (Jackson, 2019), and child peers (Golsteyn et al., 2021). I contribute to this literature by investigating how changes in relative labor market incentives for mothers and fathers and the associated changes in childhood environments influence children's socio-emotional development.

Second, I contribute to the literature on family decision-making and parental investments in child development. Previous work in this area predominantly focuses on mothers as the primary source of parental investments (Agostinelli and Sorrenti, 2018; Dahl and Lochner, 2012; Nicoletti et al., 2023). Therefore, this literature, by and large, neglects the dynamics of family decision-making within the context of two-parent households. However, the investigation of these dynamics is important. Even in an age of declining marriage and increasing divorce rates, 69% of all German (65% of all American) children live in households with two married parents (Federal Statistical Office, 2023; Livingston, 2018). Furthermore, the well-documented changes in relative labor market incentives for men and women suggest substantial shifts in parental resource allocations and the environments in which children grow up. In this paper, I close this gap by studying how changes in the labor market incentives of both mothers and fathers influence parents' money and time investments and the extent to which these investments influence the socio-emotional skill development of their children. Furthermore, in comparison to existing literature, that predominantly infers parental time investments from labor supply data, I can leverage detailed time-use data to provide a richer description of these intra-family adjustments.

Third, this study relates to the literature on the impact of children on gender gaps in the labor market. Recent papers have documented pronounced and long-lasting disparities in mothers' and fathers' labor market outcomes after their first child's arrival (Cortés and Pan, 2023; Kleven et al., forthcoming, 2019; Kuziemko et al., 2018). Since this "child penalty" cannot be explained "economically," i.e., by differences in (pre-birth) wages between mothers and fathers, nor "biologically," i.e., by the demands of birth and breastfeeding (Andresen and Nix, 2022; Kleven et al., 2021), researchers conjecture that gender norms are a driving force behind this pattern. Gender norms can be understood as a system of informal rules and shared beliefs about the appropriate behavior of men and women. For example, in many countries, including Germany, there is considerable concern that children suffer if mothers work (see also Figure S.1). This paper provides evidence that such shared beliefs may be misguided and that gender equality in the labor market does not have to come at the cost of detrimental effects on child development.

The remaining paper is organized as follows. In Section 2, I describe the institutional context of Germany, introduce the primary data sources, and describe the relevant samples and variables. The identification strategy is outlined in section 3, and I present results in section 4. Section 5 concludes the paper.

2 CONTEXT AND DATA

2.1 *Institutional context*

The institutional context of Germany is broadly comparable to other industrialized countries (OECD, 2016). In 2021, the median wage difference between full-time employed men and women was 14.2%, putting the gender pay gap in Germany slightly above the OECD average (11.9%) and slightly below the US (16.9%, OECD, 2023). To foster gender equality and to support the reconciliation of family and work, Germany has implemented several policy reforms in recent years. In 2007, Germany introduced a new parental leave benefit with a 67% replacement rate for pre-birth earnings. The duration is 12 months with an additional two months—the so-called "daddy months"—reserved for the partner of the primary caretaker (Raute, 2019). In addition, Germany has expanded the provision of center-based childcare significantly. In 2013, the legal claim for publicly subsidized childcare was extended from children older than three to children above age one (Felfe and Lalive, 2018). As of the school year 2026/27, public childcare provision will also include a legal claim for afternoon care in elementary schools (Federal Government of Germany, 2019). In contrast to these reforms, the German tax code disincentivizes gender equality in households by imposing high marginal tax rates on the secondary earner of the household, i.e., females in the majority of cases (Bick and Fuchs-Schündeln, 2017).

Following the outlined policy reforms and a shift in public attitudes towards a more gender-egalitarian allocation of work and home production, labor market outcomes for men and women in Germany have converged in recent decades (Olivetti and Petrongolo, 2016). Nevertheless, even today, marked differences remain—see Appendix Figure S.1, where I document the evolution of gender differences in wages, working hours, and gender role attitudes in Germany. Furthermore, even three decades after reunification in 1990, gender roles differ strongly between East and West Germany (Boelmann et al., forthcoming; Lippmann et al., 2020). While the Communist East encouraged female labor force participation through the early adoption of gender-equalizing policies, the West promoted a traditional male-breadwinner model. As a result, East Germany is characterized by less traditional gender role attitudes and less pronounced household specialization patterns than West Germany (Appendix Figure S.1).

2.2 Data

My empirical strategy combines a within-family sibling comparison with a shift-share design to capture changes in the relative earnings potential of mothers and fathers. To implement this identification approach, I use three data sources. The primary analysis is conducted on the German Socio-economic Panel (GSOEP). This data source allows for tracing families over time and constructing time-variant measures of children's socio-emotional skills and parental investments. The GSOEP sample, however, is too small to calculate potential wages based on a shift-share design. Therefore, I use the Sample of Integrated Labor Market Biographies (SIAB) and the German Microcensus (MZ) to calculate hourly potential wages, which are then matched to the GSOEP based on observable individual characteristics.

Analysis sample. The GSOEP is an annual, nationally representative survey that covers approximately 15, 000 private households and 25, 000 individuals in Germany (Goebel et al., 2019). It collects detailed information on socio-economic and demographic characteristics, income, and time-use of households. Furthermore, it contains a mother-and-child questionnaire that collects information on children's socio-emotional skills. In the analysis, I focus on the following variables.

Socio-emotional skills of children. I measure children's socio-emotional skills using the Big Five personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) and measures for externalizing and internalizing behavior.

The Big Five model is the most common taxonomy to describe personality traits and has gained widespread traction in economics.[2] The Big Five personality traits are highly predictive of important life outcomes, including education and earnings (Akee et al., 2018; Almlund et al., 2011; Mueller and Plug, 2006). For example, Andersen et al. (2020) show that conscientiousness predicts academic performance already in fourth grade. The findings of Akee et al. (2018) suggest that 1 SD changes in conscientiousness, agreeableness, and neuroticism at age 16 increase educational attainment by 0.517, 0.236, and 0.297 years, respectively. In addition, personality traits

[2]See Almlund et al. (2011) and Borghans et al. (2008) for comprehensive overview articles. See also Appendix Table S.1 for short descriptions of the Big Five personality traits.

are malleable during childhood but become more stable during young adulthood (Baker et al., 2019; Fitzenberger et al., 2021; Roberts and DelVecchio, 2000).[3] This suggests that changes to childhood personality may have lasting effects on an individual's long-term life outcomes. In the GSOEP, information on the Big Five is collected via a validated short scale administered to primary caretakers of children aged 2–3, 5–6, and 9–10 (Asendorpf and Van Aken, 2003; Weinert et al., 2007).[4] In particular, the primary caretaker separately rates each of their children in the relevant age range regarding various behaviors on an 11-point Likert scale. Each question can be mapped into one of the Big Five dimensions—see Appendix Table S.2. For each Big Five dimension, I sum the relevant responses such that higher values correspond to higher expressions of the underlying trait.[5] To account for gender-specific personality changes as children grow up, I standardize the resulting variables by child sex and age group (2–3, 5–6, and 9–10) on the full sample of children in the GSOEP.

In addition to the Big Five personality traits, I consider two alternative measures for socio-emotional skills that capture how children react to stressors: externalizing and internalizing behavior. Externalizing behavior is characterized by actions in the external world, i.e., aggressive or antisocial behavior. Internalizing behavior describes inward-looking processes, i.e., anxiety or depression. Externalizing and internalizing behaviors are highly predictive of important life outcomes. For example, Attanasio et al. (2020b) show that externalizing and internalizing behaviors measured at ages 5, 10, and 16 predict future smoking, employment, and earnings. Furthermore, Papageorge et al. (2019) show that externalizing behaviors increase earnings despite adverse effects on educational attainment. In the GSOEP, information on externalizing and internalizing behaviors is collected through the Strength and Difficulty Questionnaire (SDQ), answered by the primary caretaker of children aged 5–6 and 9–10. The SDQ is one of the most prevalent screening instruments for child mental health and contains

[3] See Appendix Figure S.2 for estimates of rank stability in children's socio-emotional skills. In line with existing literature, rank stability is low for young children (Ages 3–6) and increases slightly for older children (Ages 6–10). Appendix Table S.3 also presents estimates of intertemporal persistence in children's socio-emotional skills using a value-added approach (Del Bono et al., 2016). Persistence parameters are substantially lower than one, emphasizing the malleability of socio-emotional skills in the considered age range.

[4] Due to attrition and new survey entry, not all children are observed at each child age—see Appendix Figure S.3 for the distribution of repeated family observations in my core analysis sample.

[5] Bond and Lang (2019) show that treatment effects on outcomes measured based on Likert scales may be sensitive to alternative cardinalizations. In Appendix Figure S.4, I implement the sensitivity checks suggested in Lindqvist et al. (2020) and show that my baseline estimates are robust to a wide range of smooth convex and concave monotonic transformations of children's socio-emotional skills.

18 questions related to five sub-scales (hyperactivity, emotional problems, prosocial behavior, conduct problems, and peer problems)—see Appendix Table S.2. The sub-scales of hyperactivity and conduct problems (peer and emotional problems) can be further aggregated into scales for externalizing (internalizing) behavior (Goodman, 2001). In analogy to the Big Five personality traits, I construct summary indexes by summing relevant responses for each dimension and standardizing the resulting variables by child sex and age group (5–6 and 9–10) on the full sample of children in the GSOEP.

These measures for the Big Five personality traits and externalizing/internalizing behaviors rely on subjective assessments of mothers. Therefore, one may worry that different reporting standards of mothers, e.g., the willingness to portray their children in a positive/negative light, could confound the results. However, since my identification approach compares siblings at the same chronological age, such persistent differences in maternal reports are unlikely to bias the results. A remaining concern is that maternal assessments could change in response to the PWG. In a recent study, Del Bono et al. (2020) propose to address this concern using measurements from multiple evaluators. Unfortunately, GSOEP does not provide sufficient data for this approach. Instead, I also consider more objective measures of child outcomes that are closely related to socio-emotional skills but less susceptible to reporting biases, including children's BMI, whether they entered school on time, and whether they attended the high academic track in secondary school. The results closely replicate my main findings, bestowing confidence that maternal reporting biases do not drive my results.[6]

Parental investments. To study the pathways by which the PWG influences children's socio-emotional skills, I construct indicators for the monetary and time investments of parents.

First, I focus on the total amount of time parents devote to childcare. Evidence suggests that parental childcare is important for developing cognitive and socio-emotional skills, especially if used for educational activities (Del Boca et al., 2017; Del Bono et al., 2016; Fiorini and Keane, 2014; Hsin and Felfe, 2014). The GSOEP provides self-reported information on the number of hours mothers and fathers devote to childcare activities for all their children on a typical day

[6]Furthermore, Del Bono et al. (2020) conduct a simulation based on Baker et al. (2008) to quantify the extent of bias due to reporting artifacts in the estimated effects of universal childcare on children's socio-emotional skills. They find that bias is at most 0.03 SD, which is small enough not to overturn the main conclusions of this study.

in a work week. I sum across both parents to capture the total amount of childcare provided by both parents.

Second, I consider whether children are exposed to non-parental childcare. I distinguish between formal and informal childcare. Existing literature suggests that substituting parental care with (in)formal non-parental childcare may impact child development. However, effects are heterogeneous and vary with child and family characteristics and the quality of the non-parental care provider—see Duncan et al. (2023) for a comprehensive review of the literature. In the GSOEP, information on non-parental childcare is reported by household heads separately for each resident child, and I construct binary indicators for children's exposure to formal and informal care, respectively. Formal childcare includes trained childminders outside the parental household, center-based childcare for children below age six, and after-school care for children aged six and above. Informal childcare includes care provided by the non-resident extended family, friends, and paid in-home babysitters.

Third, I use the total disposable family income after taxes and transfers as a proxy for monetary investments in children. Family income may influence the development of children by allowing families to purchase child-centered goods and reducing parental stress. Indeed, existing evidence shows that disposable family income causally influences the cognitive and socio-emotional development of children (Agostinelli and Sorrenti, 2018; Akee et al., 2018; Dahl and Lochner, 2012; Løken et al., 2012; Nicoletti et al., 2023). In the GSOEP, household heads report monthly net family income. I use this information and convert it to annual family income in 2015 prices.

Fourth, I consider the maternal share of household earnings as a proxy for the monetary resources controlled by mothers. Existing research shows that mothers allocate a higher share of their resources to children than fathers (Duflo, 2012; Lundberg et al., 1997). Therefore, a shift in mothers' share of monetary resources may spur additional investments in children. In the GSOEP, individual earnings are self-reported by mothers and fathers and include all income from employment and self-employment. I use this information to compute the earnings share of mothers relative to both parents' total labor market earnings.

Sample restrictions. This study focuses on the relative earnings potential of mothers and fathers. Therefore, I restrict the sample to intact families with two resident working-age parents (18–63 years).[7] The empirical strategy is based on a sibling design. Therefore, I further restrict the sample to families with at least two children, and for whom I observe information on children's socio-emotional skills and parental investments at the same chronological child age. One may worry that these sample selection criteria are endogenous to the treatment of interest. For example, it could be the case that decreases in the PWG increase the likelihood of parental separation or decrease the likelihood of having a sibling. In Appendix Table S.4, I show that this is not the case: in my sample 4% (13%) of families separate (have additional children) within the next 5 years. However, the likelihood of separation (additional children) is not affected by the PWG.

Lastly, I restrict the analysis to the years 2005–2019. 2005 marks the first year GSOEP collected data on children's socio-emotional skills; 2019 marks the last year before the outbreak of the COVID-19 pandemic.

Descriptive statistics for the resulting sample are provided in Table 1. The core analysis sample comprises $5,484$ child-year observations and $2,519$ sibling groups. The number of sibling groups is less than half the child-year observations because I allow for sibling groups that contain more than two siblings, i.e., triplets, quadruples, etc. The sample is gender-balanced, and 19% of children reside in East Germany. The average child in the sample is 6.2 years old and the second-born in its family. The sample shows a slightly positive selection in terms of child outcomes. For example, the sampled children are more conscientious and show less externalizing and internalizing behavior than the average child in the population. Mothers and fathers devote 9.9 hours to childcare on a typical workday.[8] Furthermore, 66% (29%) of children are exposed to non-parental formal (informal) childcare regularly. Mothers, on average, contribute 19% of household earnings, which reflects their lower labor market participation and the con-

[7] I define intact families as follows: children must be the biological or adopted child of the mother, or the mother's partner. The two parent figures in the household have to be the same individuals across the time period of the sibling comparison. Hence, I allow for non-biological family relationships and disregard parents' marital status. In section 4.3, I show that my results remain unchanged when focusing on biological families or married parents only.

[8] In Appendix Table S.6, I compare childcare time in the GSOEP with measures of childcare time in the German Time-Use Study (GTUS). The GTUS distinguishes between childcare as a primary activity, e.g., homework, reading, sports and play, and any activities where the child is present. The comparison suggests that childcare time in the GSOEP is best understood as a broad measure capturing any activity where the child is present.

TABLE 1 – Summary statistics

	N=5,484; Sibling groups=2,519			
	Mean	SD	Min	Max
Panel (a): Child characteristics				
Female	0.49	0.50	0.00	1.00
Migration background	0.02	0.12	0.00	1.00
East Germany	0.19	0.40	0.00	1.00
Age	6.18	2.86	2.00	10.00
Birth rank	2.05	1.03	1.00	8.00
Panel (b): Child socio-emotional skills				
Openness	0.04	0.97	-4.24	1.29
Conscientiousness	0.07	0.95	-2.81	2.09
Extraversion	-0.02	0.99	-3.93	1.27
Agreeableness	0.01	0.97	-3.31	2.08
Neuroticism	-0.02	0.98	-1.64	2.99
Externalizing	-0.12	0.95	-1.77	3.66
Internalizing	-0.10	0.98	-1.55	3.90
Panel (c): Parental investments				
Parental care (hours/day)	9.89	5.20	0.00	32.00
Formal care (yes/no)	0.66	0.48	0.00	1.00
Informal care (yes/no)	0.29	0.46	0.00	1.00
Total disp. family income (in Thsd. €)	46.02	25.99	6.54	568.49
Share maternal earnings (in %)	19.20	22.99	0.00	99.08

Data: GSOEP.
Note: Own calculations. This table shows summary statistics for the core analysis sample. The sample spans the years 2005 to 2019. It includes two-parent households aged 18–63 with at least two resident children aged 2–10. The sample only includes child-year observations with at least one valid measurement of socio-emotional skills (see Panel [b]) and valid measurements of all parental investments (see Panel [c]).

tinued existence of gender wage gaps in Germany (Appendix Figure S.1). In Appendix Table S.5, I compare the families of my core sample to alternative samples that are not restricted to (i) the availability of children's socio-emotional skills, and (ii) the availability of sibling data. This comparison shows that my core sample is broadly comparable to these less restricted samples in terms of child characteristics and parental investments.

Potential wages. I approximate the differential changes in labor market incentives for mothers and fathers by calculating potential wages for different socio-demographic groups in Germany. These potential wages are constructed using two data sources.

The Sample of Integrated Labor Market Biographies (SIAB). The SIAB is an administrative data set compiled by the research institute of the Federal Employment Agency of Germany.It contains a 2% random sample of Germans who are either employed, recipients of social benefits, or job-seeking. It does not include self-employed workers and civil servants (Froderman et al., 2021). The SIAB provides information on daily wages that are right-censored at the cap for social security contributions. In my baseline analyses, I follow Dustmann et al. (2009) and impute the upper tail of the wage distribution by draws from a truncated log-normal distribution (Gartner, 2005).[9] The data are organized in spells, allowing researchers to trace the labor market biographies of individuals. I use information about an individual's establishment to aggregate employment spells to job cells where each cell represents one job per individual in a given year.

I restrict the SIAB to working-age individuals (18–63 years) who pay social security contributions. As a result, I obtain a data set with $\approx 595,000$ job observations per year. For each job, I observe daily wages, the sector, and the worker's socio-demographic characteristics.

The German Microcensus (MZ). The MZ is an annual household survey covering 1% of all German households and collects information on family socio-demographics, income, and living conditions (GESIS, 2020). In contrast to the SIAB, it also has information on working hours.

To match the sample composition of the SIAB, I restrict the MZ to employed individuals of working age (18–63 years) and exclude individuals who are either self- or marginally employed (<10h/week).[10] I obtain a data set with $\approx 174,000$ job observations per year. For each job, I observe working hours, the sector, and the worker's socio-demographic characteristics.

Constructing potential wages. The general idea of my shift-share design is to predict group-specific potential wages based on sectoral shocks and the group's exposure to such shocks. Specifically, I calculate the potential wage of group g in year t as follows:

$$\hat{w}_{gt} = \sum_{s} \underbrace{\frac{E^{s}_{g,1995}}{E_{g,1995}}}_{(1)} \times \underbrace{w^{s}_{t}}_{(2)} . \tag{1}$$

[9] In section 4.3, I show the robustness of my results to different imputation assumptions.

[10] Appendix Tables S.7 and S.8 show that the resulting samples of the SIAB and the MZ are comparable in terms of the industries and occupations of the represented jobs and the socio-demographic composition of workers.

Term (1) of equation 1 indicates the employment share of sector s in group g in the base year 1995. Term (2) of equation 1 indicates the average hourly wage paid in sector s at the national level in year t. Hence, the group-specific potential wage $\hat{w}_{gt}$ is a weighted average of wages paid in different sectors of the economy where weights are given by the historic employment exposure of groups to these sectors in 1995.

Groups g are defined by partitioning the German population into 576 cells. These cells are pinned down by two expressions of gender, three education levels, and 96 regional units. The low-education group includes individuals who have, at most, a low-track secondary degree and no vocational training. The intermediate education group includes individuals with a low-track secondary degree plus vocational training, and individuals with a high-track secondary degree but no further tertiary education. The high-education group consists of people with tertiary education at the university level. The 96 regional units correspond to Germany's spatial planning regions. Spatial planning regions describe economic centers and their surroundings nested within the 16 federal states of Germany. Since commuter flows are an essential criterion for defining spatial planning regions, I refer to them as commuting zones (CZ).

Employment sectors s are defined by grouping employed individuals into 22×14 occupation-industry cells based on the German Classification of Occupations 2010 (KldB10) and the German Classification of Activities 2008 (WZ08).

Based on these definitions, I calculate potential wages as follows. First, I compute historic employment shares for groups g in 1995 using data from the SIAB (Term [1] of equation 1).[11] Second, I calculate sector-specific hourly wages in year t combining data from the SIAB and the MZ (Term [2] of equation 1).[12] Specifically, I divide the average daily wage in sector s at time t (calculated from the SIAB) by the corresponding average daily working hours (calculated from the MZ): $w_t^s = d_t^s / h_t^s$. These averages are computed by excluding the CZ of interest ("leave-one-out") to avoid mechanical relationships.[13]

[11] Appendix Tables S.9 and S.10 document the sorting of gender and education groups into industries and occupations in 1995.

[12] Appendix Figure S.5 shows distributions of cell sizes for the calculation of Terms (1) and (2) of equation 1.

[13] The MZ provides geographic identifiers at the level of federal states only. Therefore, I match average daily wages at the national level that leave out a particular CZ with average daily working hours at the national level that leave out the entire federal state in which the CZ is nested.

Sample restrictions. I match potential wages to the GSOEP based on an individual's gender, education, and CZ of residence. To ensure that the wage shock had been realized when respondents answered the GSOEP survey, I match GSOEP parents to their potential wage in $t-1$. As a result, I obtain a sample of potential wages that covers 576 socio-demographic groups over the period 2004–2018.

Figure 1 displays changes in potential wages by gender and education group across CZs in Germany throughout this period. All figures are normalized by the period-specific average growth rate to account for secular wage trends that affect all socio-demographic groups in a given period. Blue (red) areas indicate changes in favor of female (male) potential wages. Darker (lighter) colors indicate more (less) positive changes for both genders. Figure 1 shows substantial heterogeneity in the evolution of male and female potential wages across regions and education groups. For example, in the aftermath of the financial crisis (2008–2011), low-educated women experienced lower potential wage gains than low-educated men. In contrast, high-educated women experienced higher potential wage gains than high-educated men. Furthermore, we observe marked regional heterogeneity in wage growth patterns across CZs for all years and education groups.

3 EMPIRICAL STRATEGY

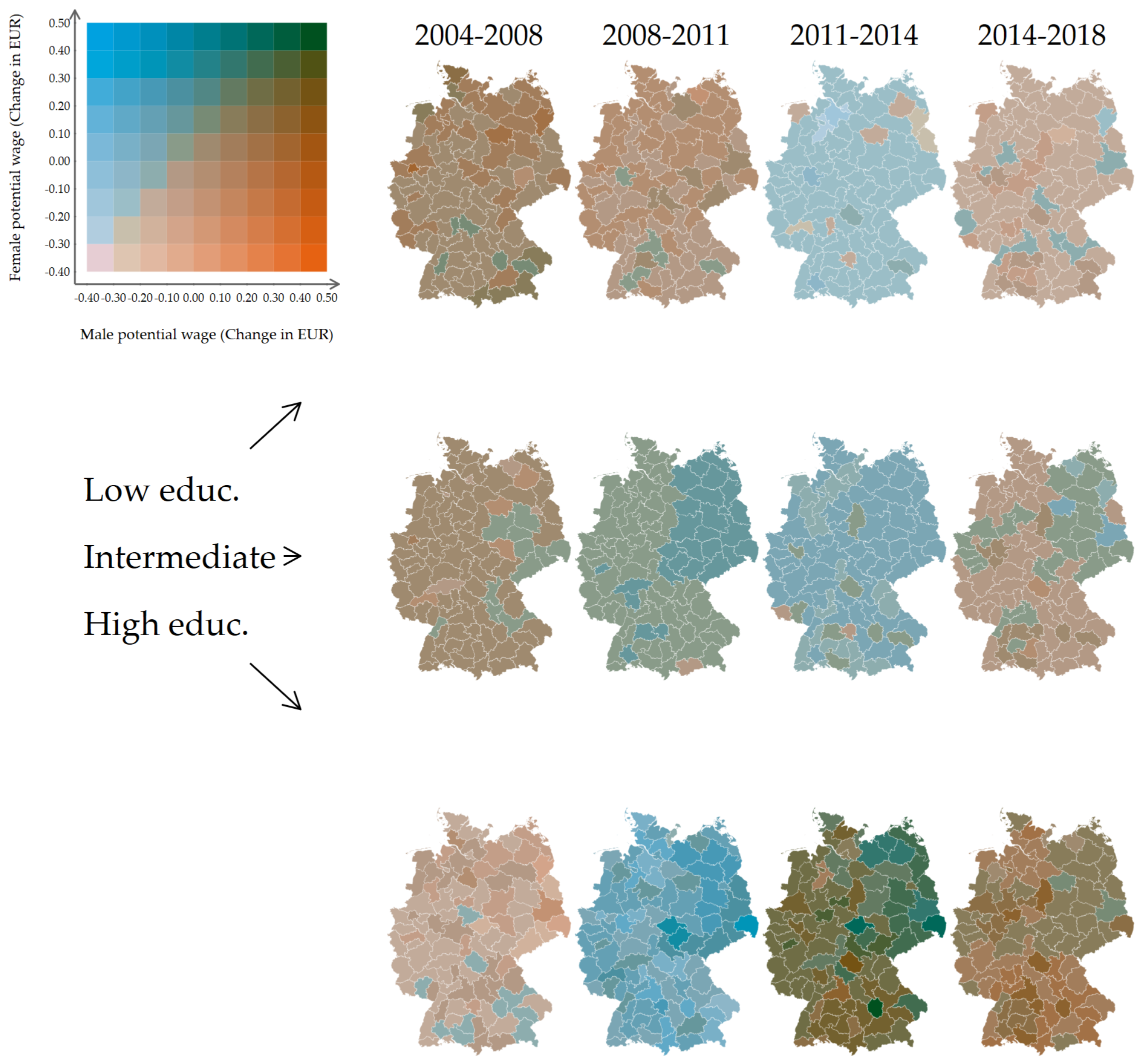
Identification strategy. I am interested in the causal effect of maternal and paternal earnings potential on the development of socio-emotional skills in children, as well as the monetary and time investments through which parents may influence the production of these skills. Given the panel structure of the GSOEP, the unit of observation is child i in year t.

Consider the following ordinary least squares (OLS) regression:

$$y_{it} = \alpha + \beta^m \ln w_{it}^m + \beta^p \ln w_{it}^p + \epsilon_{it}, \tag{2}$$

where y_{it} denotes any outcome of interest, w_{it}^m and w_{it}^p denote the observed wages of mothers and fathers, and ϵ_{it} the error term.

FIGURE 1 – Change in potential hourly wages of men and women by education and commuting zone, 2004–2018



Data: SIAB, MZ.
Note: Own calculations. This figure shows changes in the potential wages of men and women by education level and commuting zone. For each time period, changes are normalized by the period-specific average growth rate. Potential wages are calculated according to equation 1. The 96 commuting zones are defined by the official territory definition of spatial planning regions of the Federal Office for Building and Regional Planning. Education is classified as follows: Lower secondary degree without tertiary education (*Low*), lower secondary degree with vocational training or higher secondary degree without vocational training (*Intermediate*), university qualification (*High*).

The regression in equation 2 would estimate the causal effect of maternal and paternal earnings potential if w_{it}^{m} and w_{it}^{p} were assigned randomly across children and time. Under such a wage assignment process, observed wages would be uncorrelated with family and child characteristics and time trends. Furthermore, since observed wages would be independent of the labor supply decisions of parents, they would provide an accurate representation of maternal and paternal earnings potentials. In reality, observed wages are not assigned randomly but vary with many factors, including parental ability, business cycle fluctuations, and parental labor supply decisions. Therefore, the identification assumption implicit in equation 2 may be violated through joint determinants of the variables of interest and reverse causality.

To address these threats to identification, I estimate the following model instead:

$$y_{it} = \alpha + \beta^m \ln \hat{w}^m_{it-1} + \beta^p \ln \hat{w}^p_{it-1} + \gamma_{f(i)a(it)} + \tau_t + X'_{it}\delta + \epsilon_{it}. \tag{3}$$

First, I replace observed wages w^m_{it} and w^p_{it} with potential wages $\hat{w}^m_{it-1}$ and $\hat{w}^p_{it-1}$ to rule out concerns about reverse causality. For example, one may worry that parents adjust their labor supply and wages in response to the socio-emotional development of their children. Potential wages that capture wage variation due to group-specific labor demand rather than to endogenous parental labor supply decisions, effectively address this concern (Bartik, 1991).[14] As mentioned in section 2, I use lagged instead of contemporaneous potential wages to ensure that the wage shock had been realized when respondents answered the GSOEP survey.

Second, I include a vector of family times child age fixed effects, $\gamma_{f(i)a(it)}$, that absorbs all confounding factors nested in differences across families at a specific child age a. For example, one may worry about confounding via time-constant family differences in gender norms (Boelmann et al., forthcoming; Lippmann et al., 2020), assortative matching of parents (Eika et al., 2019), genetic endowments (Demange et al., 2021), but also family differences that are specific to different child ages such as the productivity of parental time investments (Del Boca et al., 2014). The inclusion of $\gamma_{f(i)a(it)}$ takes care of such concerns.

Third, I include a vector of year fixed effects, τ_t, to control for secular trends such as the decline of gender wage gaps in Germany (Appendix Figure S.1). For example, one might be concerned that the within-family sibling comparison confounds the effect of changes in the PWG with children's birth cohort and parental age effects. This concern would be relevant if the PWG was smaller for children from later birth cohorts (or for older parents at the time of birth) than

[14] Shift-share (or Bartik) designs are widely used in the literature on household decision-making (Anderberg et al., 2015; Autor et al., 2019; Bertrand et al., 2015; Bruins, 2017; Schaller, 2016; Shenhav, 2021) and child development (Agostinelli and Sorrenti, 2018; Aizer, 2010; Lindo et al., 2018; Page et al., 2019).

for their siblings from earlier cohorts (or for younger parents at the time of birth). Including τ_t in addition to $\gamma_{f(i)a(it)}$ takes care of such concerns. To see this, note that the child's birth cohort is a linear combination of age a and year t. Analogously, parental age is a linear combination of the parental birth cohort and year t. $\gamma_{f(i)a(it)}$ fixes both the child age and the birth cohort of parents while τ_t fixes the year of comparison. Therefore, the joint inclusion of $\gamma_{f(i)a(it)}$ and τ_t holds the child's birth cohort and parental age constant and rules them out as confounding factors (Black et al., 2018; McGrath et al., 2014).

While the inclusion of $\gamma_{f(i)a(it)}$ and τ_t are important for identification, one may worry that these high-dimensional fixed effects absorb much of the variation and lead to non-random selection into the identifying sample (Miller et al., 2023). The scope of this concern is limited in this study since the treatment variables are continuous, assuring sufficient intra-family variation in the right-hand side variables. I will report R^2-statistics in all regressions tables showing considerable variation in the outcomes of interest even after conditioning on $\gamma_{f(i)a(it)}$ and τ_t.[15]

Equation 3 can be easily transformed to capture changes in the relative earnings potentials of mothers and fathers:

$$y_{it} = \alpha + \beta^{\Delta}\underbrace{(\ln \hat{w}^{m}_{it-1} - \ln \hat{w}^{p}_{it-1})}_{=\hat{w}^{\Delta}_{it-1}} + \beta^{\Sigma}\underbrace{(\ln \hat{w}^{m}_{it-1} + \ln \hat{w}^{p}_{it-1})}_{=\hat{w}^{\Sigma}_{it-1}} + \gamma_{f(i)a(it)} + \tau_t + X'_{it}\delta + \epsilon_{it}, \qquad (4)$$

where $\hat{w}^{\Delta}_{it-1}$ represents the PWG and $\hat{w}^{\Sigma}_{it-1}$ is an essential control to isolate the effect of relative earnings potentials net of differences in wage levels. The baseline specification, does not include additional time-varying individual-level controls X'_{it}. However, in section 4.3, I show that the results are robust to richer specifications of X'_{it}.

All specifications are estimated by OLS, and standard errors are clustered by family f. In section 4.3, I show that the resulting standard errors are not systematically different from standard errors based on alternative cluster definitions.[16]

[15] See also Appendix Figure S.6 for raw data plots after residualizing a selection of outcomes and the treatment variables of interest from $\gamma_{f(i)a(it)}$ and τ_t.

[16] An alternative research design would instrument observed wages with potential wages. To do so, one needs to restrict the sample to mothers and fathers with available wage information in all relevant time periods. This restriction is prohibitive since many young mothers transition in and out of the labor force when their children are young. For example, in my core analysis sample only 59% of mothers are active in the labor market.

Identification assumption. The econometric properties of shift-share designs have been investigated in several recent methodological papers (Adão et al., 2019; Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020; Jaeger et al., 2018). Causal identification in shift-share designs can either be based on the exogenous assignment of the "shares," i.e., term (1) of equation 1, or the "shifters," i.e., term (2) of equation 1. In the case of exogenously assigned "shares," the shift-share design is reminiscent of a difference-in-differences design with many treatments: the "shares" define the treatment assignment, and the "shifters" define the treatment. In this paper, I follow the "share"-interpretation suggested by Goldsmith-Pinkham et al. (2020) and discuss the identification assumption in terms of exogenously assigned sector shares in the base year 1995. Therefore, in analogy to a difference-in-differences design, the identification assumption can be stated as follows:

$$\begin{aligned} &Cov\left(\epsilon_{it}, \frac{E^s_{g,1995}}{E_{g,1995}} \middle| \gamma_{f(i)a(it)}, \tau_t\right) = 0, \\ &\forall\, s \in S, \\ &\forall\, t \geq 1995 + 10. \end{aligned} \tag{5}$$

Note that the base year 1995 precedes the time frame of my analysis (2005–2019) by at least ten years. Furthermore, due to the inclusion of $\gamma_{f(i)a(it)}$, the identifying variation comes from within-family changes over time.[17] Hence, the identification assumption in equation 5 implies that group-specific sector shares in 1995 need to be uncorrelated to *sibling differences* in the error term a decade later or more. This identification assumption would be violated if the historic sector shares correlated with other factors that predict contemporaneous intra-family variation in children's socio-emotional skills.

I assess the plausibility of this identification assumption as follows. First, following standard procedures for sibling fixed effect designs (e.g., Black et al., 2020; Deming, 2009), I show that the within-family treatment variation is uncorrelated with a large set of child characteristics that predict their socio-emotional skills and parental investments (Appendix Table S.11). For this illustration, I restrict my analysis sample to sibling pairs, i.e., I exclude triplets and higher-order sibling groups. Then, I assign siblings to a "High-PWG" ("Low-PWG") group if their

[17] Note that potential wages *in levels* are unlikely exogenous because they reflect variation in parent's educational attainment, region of residence, and biological sex (Equation 1).

PWG at age a is higher (lower) than the corresponding PWG of their sibling. Panel (a) of Table 2 contrasts the "High-PWG" and the "Low-PWG" groups in terms of their observable characteristics. Columns 1–3 show differences in observable characteristics after netting out family

TABLE 2 – Within-family variation of characteristics by treatment status

	N	Family × child age FE			Family × child age FE + Year FE		
		High-PWG (1)	Low-PWG (2)	Δ (3)	High-PWG (4)	Low-PWG (5)	Δ (6)
Panel (a): Sibling characteristics							
Female	4,264	0.480	0.488	0.008 (0.016)	0.483	0.489	0.006 (0.017)
Born before October	4,264	0.789	0.782	-0.007 (0.012)	0.789	0.782	-0.007 (0.014)
Birth year	4,264	2006.659	2007.359	0.701*** (0.070)	2007.710	2007.710	–
Firstborn	4,264	0.587	0.432	-0.155*** (0.019)	0.369	0.359	-0.010 (0.014)
# of siblings	4,264	2.533	2.575	0.042*** (0.009)	2.606	2.600	-0.007 (0.009)
Birth height (cm)	2,222	50.824	50.921	0.096 (0.103)	50.958	50.965	0.007 (0.108)
Birth weight (kg)	2,236	3.266	3.296	0.030* (0.018)	3.299	3.307	0.008 (0.018)
Days in hospital (3 months post-birth)	2,222	2.221	2.202	-0.020 (0.302)	2.056	2.146	0.091 (0.284)
Age at birth (Mother)	4,264	29.824	30.524	0.701*** (0.070)	30.875	30.875	–
Age at birth (Father)	4,264	33.105	33.810	0.705*** (0.071)	34.152	34.158	0.007 (0.013)
Panel (b): Treatment variables							
Potential wage (Father)	4,264	15.045	14.884	-0.161*** (0.017)	15.064	14.891	-0.174*** (0.016)
Potential wage (Mother)	4,264	13.883	13.917	0.034** (0.014)	13.884	13.917	0.033*** (0.006)
PWG	4,264	-1.162	-0.967	0.194*** (0.011)	-1.180	-0.974	0.206*** (0.017)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows differences in sibling characteristics conditional on different controls. All coefficients are estimated on the core sample described in Table 1 (restricted to sibling pairs). Siblings are allocated to the *High-PWG* (*Low-PWG*) group if they are subject to a higher (lower) value of the PWG than their sibling. The left-hand panel controls for family times child age fixed effects. The right-hand panel additionally controls for year fixed effects. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

times child age fixed effects $\gamma_{f(i)a(it)}$. As expected, both groups are comparable in characteristics assigned independently of their birth cohort, e.g., gender and birth month. However, on average, children of the "Low-PWG" group are born later, are less likely to be the firstborn, and have more siblings and older parents. These differences reflect the concern that a simple within-family sibling comparison confounds the effect of changes in the PWG with birth cohort and parental age effects. To address this concern, I additionally partial out time fixed effects τ_t. Columns 4–6 show that the joint inclusion of $\gamma_{f(i)a(it)}$ and τ_t make siblings comparable in all considered dimensions: as the child's birth cohort (parental age) is a linear combination of child age a (parental birth cohort) and year t, sibling differences related to their birth cohort and parental age at birth vanish. Importantly, Panel (b) of Table 2 shows that even after conditioning on this rich set of fixed effects, there remains sizable within-family variation in the treatment variables: the PWG difference between the "High-PWG" and the "Low-PWG" groups amounts to roughly 20% of the sample mean. These within-family differences in the treatment variables provide the identifying variation for my estimates.

Second, I assess the sensitivity of my estimates to violations of the identification assumption concerning particular sectors of the economy. Goldsmith-Pinkham et al. (2020) show that shift-share estimates can be decomposed into just-identified, group-specific instrumental variable coefficients and their corresponding Rotemberg weights.[18] Rotemberg weights are helpful indicators to make the origin of the identifying variation transparent. Intuitively, if Rotemberg weights are highly concentrated in one sector, estimates may be biased by other shocks affecting groups specializing in this sector. Appendix Table S.12 provides an overview of the top ten economic sectors for mothers and fathers ranked by their Rotemberg weights. For mothers, most of the identifying variation comes from low-skill purchasing and sales occupations in wholesale and retail ($\approx$ 11%), low-skill logistics occupations in business services ($\approx$ 8%), and education and social care occupations ($\approx$ 7%). For fathers, most identifying variation comes from high-skill machine-building occupations in the manufacturing sector ($\approx$ 17%), low-skill workers in the construction sector ($\approx$ 11%), as well as high-skill IT occupations in business services ($\approx$ 4%). In general, the relatively wide dispersion of Rotemberg weights shows that my results are driven by many different sectors of the economy, suggesting a low sensitivity of

[18] Thus, my identification relies on 308 instruments ($= 22 \times 14$ occupation-industry cells) for each group.

my estimates to sector-specific violations of the identification assumption stated in equation 5.

Lastly, I confirm that $\hat{w}^m_{it-1}$ and $\hat{w}^p_{it-1}$ are good proxies for the earnings potential of mothers and fathers. While the actual earnings potential of mothers and fathers are unobserved, I can compare $\hat{w}^m_{it-1}$ and $\hat{w}^p_{it-1}$ to the corresponding observed wages w^m_{it} and w^p_{it} in the analysis sample. If potential wages capture relevant information on earnings potential, we expect them to be strongly predictive of their observed analogs. Figure 2 shows the residual correlation of potential wages and observed wages after accounting for individual and year fixed effects. There is a strong correlation between within-person changes in potential wages and their observed analogs. Furthermore, potential wages remain predictive for observed wages up to four years into the future (Appendix Figure S.7).[19] This result shows that estimates of potential wages are good proxies for the actual earnings potential of mothers and fathers.

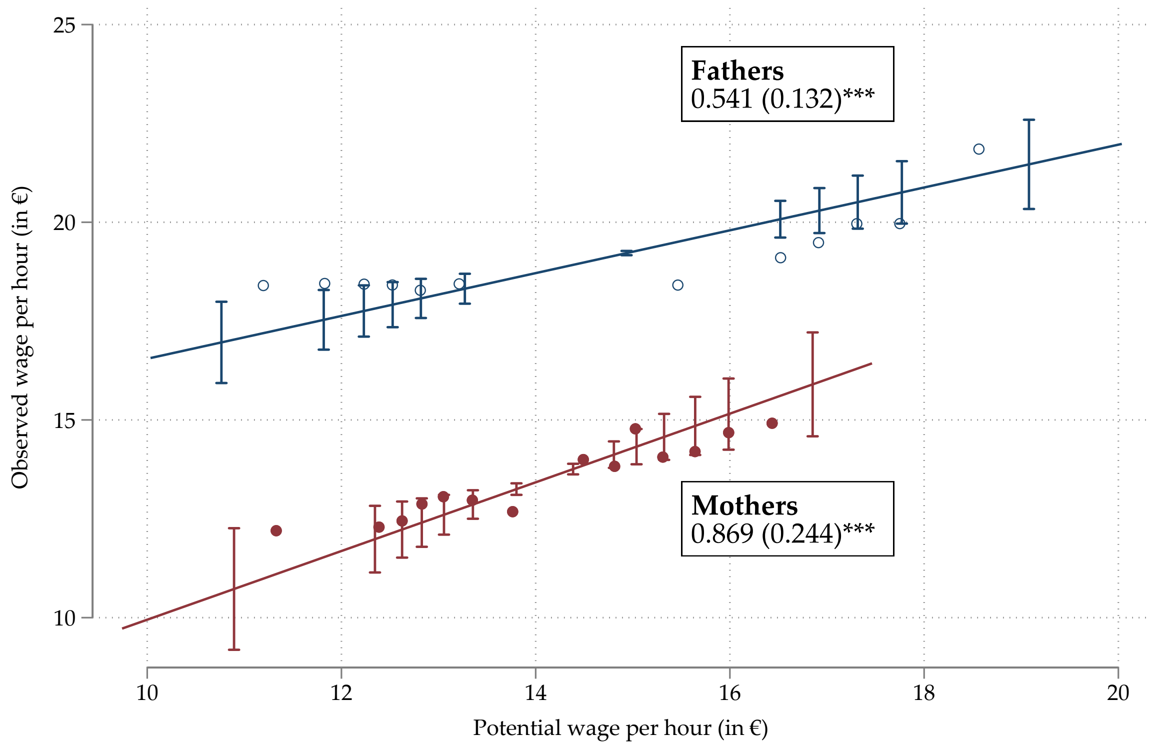
To summarize the previous discussion, my identifying variation comes from within-family changes in potential wages. These changes in potential wages are predictive of actual changes in parental wages and uncorrelated to differences in sibling characteristics. Additionally, the identifying variation is spread over many sectors of the economy, mitigating the risk that sector-specific violations of the identification assumption bias the results.

4 RESULTS

I present the results in four steps. First, I illustrate how mothers and fathers allocate their time to different activities in response to changes in their earnings potential. This step provides a proof of concept showing that German households respond to labor market incentives. Furthermore, it suggests changes in children's living environment that may affect their socio-emotional development. Second, I present the effects of changes in the PWG on the socio-emotional skills of children. Third, I assess the robustness of these findings. Lastly, I analyze the mechanisms through which changes in the PWG affect children's socio-emotional skills by analyzing its effect on the monetary and time investments of parents and by conducting a heterogeneity analysis.

[19]The impact of the shock is more permanent for fathers than for mothers which can be rationalized by mother's flexible labor force attachment when their children are young.

FIGURE 2 – Within-person correlation of potential and observed wages



Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows the relationship between within-person changes in potential wages and within-person changes in observed wages for mothers and fathers. The sample spans the years 2005 to 2019 and includes two-parent households aged 18–63 with a resident child aged 2–10. Solid lines show estimates from a linear regression of actual wages on potential wages controlling for individual fixed effects and year fixed effects. Whiskers show 95% confidence intervals; standard errors are clustered at the individual level. Binned scatters are constructed using the optimal binning procedure of Cattaneo et al. (2024).

4.1 Parental time allocation

Table 3 presents the effects of changes in maternal and paternal potential wages on four categories of parental time-use during a regular work week: work for pay (incl. travel time to and from work), childcare, housework activities (incl. repairs and errands), and personal time (incl. hobbies and education). Outcomes are measured in hours per day. For ease of interpretation, I rescale the coefficients from all regressions to represent the effect of a 10% increase in potential wages of mothers and fathers.

Mothers have a positive own-wage elasticity of labor supply: a 10% increase in maternal potential wages increases their work time by 1.2 hours per day (Column 1). This effect reflects strong increases at the extensive margin whereas the effect on mothers who are in work already is

TABLE 3 – Parental wages and parental time allocations

	Mother (hours per day)				Father (hours per day)			
	Work for pay (1)	Child-care (2)	House-work (3)	Personal time (4)	Work for pay (5)	Child-care (6)	House-work (7)	Personal time (8)
Effect of 10% ↑ in parental wages								
Mother	1.230*** (0.375)	-0.053 (0.520)	-0.228 (0.331)	-0.737*** (0.258)	-0.181 (0.572)	0.162 (0.350)	0.144 (0.261)	-0.309 (0.286)
Father	-0.482*** (0.156)	0.424* (0.229)	0.229* (0.135)	-0.029 (0.061)	0.498** (0.224)	0.150 (0.194)	-0.034 (0.109)	-0.334** (0.166)
Family × child age FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	5,484	5,484	5,484	5,484	5,484	5,484	5,484	5,484
R^2	0.798	0.753	0.744	0.657	0.778	0.712	0.729	0.681
Outcome Mean	3.413	7.513	4.576	1.198	8.743	2.381	2.066	1.196
Outcome SD	3.456	4.265	2.228	1.286	3.208	2.412	1.766	1.391

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental time allocations in response to changes in maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

not distinguishable from zero (Appendix Table S.13).[20] The implied total hours elasticity are large, which, however, is consistent with the well-documented sensitivity of young mothers to temporal changes in their wages (Attanasio et al., 2018). The increase in work for pay does not lead to downward revisions in the time mothers allocate to childcare and housework (Columns 2 and 3). Instead, most of the increase in labor market activity is accounted for by decreased time for hobbies and education: a 10% increase in maternal potential wages decreases personal time by 0.7 hours per day (Column 4). These patterns suggest that German mothers respond to increased labor market opportunities by spending more time at work while protecting the overall time with their children. This conclusion is further supported by descriptive evidence from German time-use diaries. In Appendix Figure S.9, I compare the share of mothers at work with the share of mothers spending time with their children for each 10-minute window of the day across the survey waves 2001/02 and 2012/13. Over time, there has been an increasing share of mothers at work during business hours (8 am–4 pm) and a corresponding decrease

[20]Quantile regressions show that the effects are evenly distributed across the hours distribution, suggesting that mothers who are shifted into employment take up both part-time and full-time jobs (Appendix Figure S.8).

in the share of mothers who spend time with their children. However, this trend is offset by an increase in the share of mothers spending time with their children in the late afternoon and evening hours (4 pm–8 pm). This evidence suggests that mothers compensate their children for their absence during the day with increased interactions after they return from work.[21]

Fathers also have a positive but smaller own-wage elasticity of labor supply: a 10% increase in paternal potential wages increases their work time by 0.5 hours per day (Column 5). This effect reflects increases at the intensive margin whereas the effect on the extensive margin is not distinguishable from zero (Appendix Table S.13). Like mothers, their increased labor market activity is accounted for by decreased time for hobbies and education: a 10% increase in paternal potential wages decreases personal time by 0.3 hours per day (Column 8).

Furthermore, Table 3 shows that mothers and fathers react asymmetrically to changes in the potential wage of their partners. On the one hand, mothers respond to increases in paternal wages by reallocating time from work to childcare: holding their own potential wages constant, a 10% increase in paternal potential wages decreases maternal working time by 0.5 hours per day (Column 1), allowing mothers to increase childcare activities by a similar amount (Column 2). On the other hand, fathers' response to changes in their partner's potential wages is more attenuated and cannot be statistically distinguished from zero.

These analyses show that parents respond to labor market incentives by adjusting their time allocations with likely consequences for the environment in which children grow up. Furthermore, the responsiveness of maternal time allocations to changes in the potential wages of their partner illustrates the importance of considering the labor market incentives of both mothers and fathers—an aspect that is underrepresented in the current literature on child development where the exclusive focus on mothers as primary caretakers is prevalent.

[21] See Hsin and Felfe (2014) for similar results from the US. They also show that mothers especially protect time for quality interactions with children. This finding may assuage concerns that mothers maintain the "quantity" of time investments at the cost of "quality." Data limitations prevent me from replicating their analysis in my sample.

4.2 *Children's socio-emotional skills*

The upper panel of Table 4 displays the effects of maternal and paternal potential wages on children's socio-emotional skills (see equation 3). Measures for socio-emotional skills are standardized on the estimation sample to have a mean of zero and an SD of one. I again rescale the coefficients to represent the effect of a 10% increase in potential wages of mothers and fathers.

TABLE 4 – Parental wages and children's socio-emotional skills

	Big Five Personality Traits					Strength and Difficulty Questionnaire	
	Openness (1)	Conscientiousness (2)	Extraversion (3)	Agreeableness (4)	Neuroticism (5)	Externalizing (6)	Internalizing (7)
Panel (a): Effect of 10% ↑ in parental wages							
Mother	-0.109	0.001	0.221**	-0.046	0.093	0.266	0.081
	(0.119)	(0.127)	(0.108)	(0.113)	(0.172)	(0.236)	(0.131)
	[0.362]	[0.995]	[0.040]	[0.684]	[0.589]	[0.261]	[0.536]
	{0.985}	{1.000}	{0.552}	{1.000}	{1.000}	{0.970}	{1.000}
Father	-0.044	0.024	0.005	0.033	0.063	-0.096	0.128
	(0.068)	(0.059)	(0.073)	(0.065)	(0.144)	(0.108)	(0.127)
	[0.515]	[0.690]	[0.946]	[0.609]	[0.662]	[0.377]	[0.314]
	{1.000}	{1.000}	{1.000}	{1.000}	{1.000}	{0.985}	{0.985}
Panel (b): Effect of 10% ↓ in PWG							
PWG	-0.032	-0.011	0.108*	-0.040	0.015	0.181	-0.024
	(0.069)	(0.070)	(0.064)	(0.066)	(0.112)	(0.136)	(0.091)
	[0.639]	[0.871]	[0.090]	[0.545]	[0.894]	[0.183]	[0.795]
	{0.960}	{0.980}	{0.453}	{0.960}	{0.980}	{0.657}	{0.980}
Family × child age FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
N	5,443	5,453	5,443	5,432	3,597	2,273	2,262
R^2	0.556	0.559	0.495	0.542	0.506	0.615	0.614
Outcome Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outcome SD	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in children's socio-emotional skills in response to changes in maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects. Regressions in Panel (b) also control for the sum of maternal and paternal potential wages. Standard errors (in parentheses) are clustered at the family level. p-values are presented in brackets. p-values that control the family-wise error rate (FWER) are presented in curly brackets. FWER-adjusted p-values are calculated based on the Romano-Wolf step-down procedure using 200 bootstrap replications (Clarke et al., 2020). Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In general, there is limited evidence for parental labor market incentives to affect children's socio-emotional skills. 13 of the 14 estimated coefficients cannot be distinguished from zero at conventional levels of statistical significance. An exception is the effect of maternal potential wages on children's extraversion: a 10% increase in maternal potential wages increases children's extraversion by 0.22 SD (Column 3). However, the significance of this result vanishes once we account for multiple hypothesis testing. Using the Romano-Wolf step-down procedure of Clarke et al. (2020) to control for the family-wise error rate (FWER) of the 14 tested hypotheses, the p-value for the effect of maternal potential wages on extraversion drops from 0.04 to 0.55.

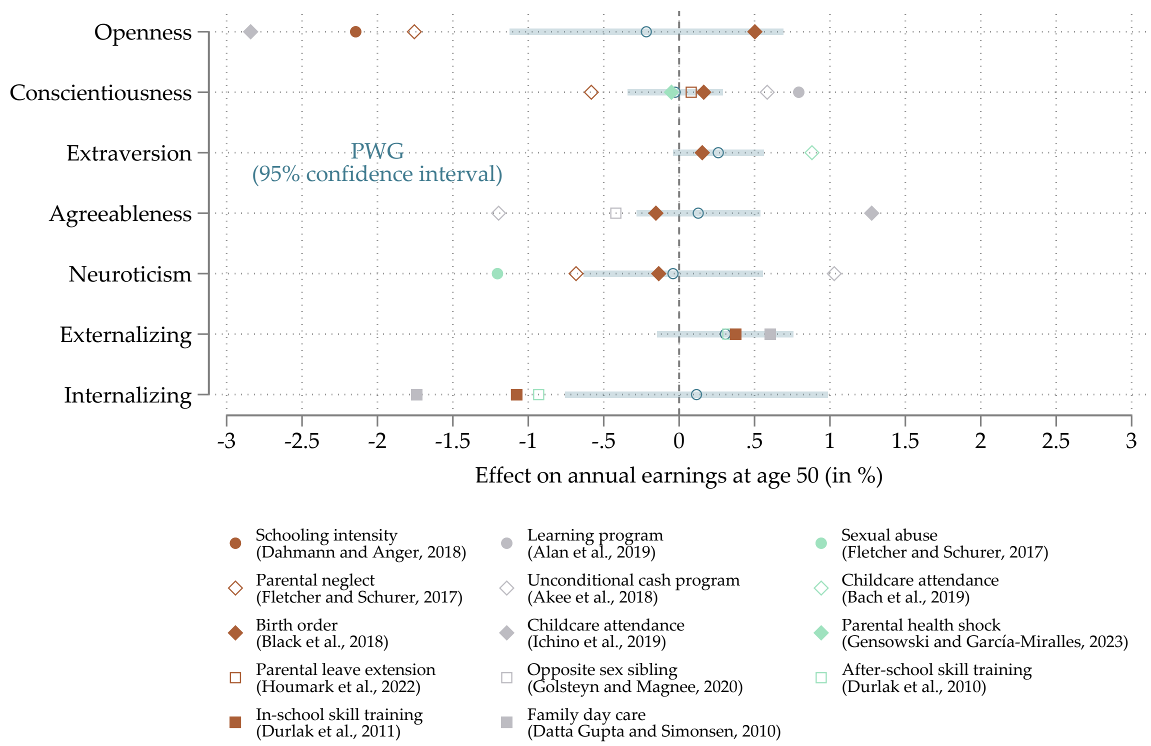
The lower panel of Table 4 displays the effect of the PWG on children's socio-emotional skills. The PWG is calculated as the log ratio of maternal and paternal potential wages. To isolate the effect of relative wages from the effects of wage levels, I control for the total of maternal and paternal wages in all regressions (see equation 4). Coefficients are scaled to reflect a 10% decrease in the PWG.

There is limited evidence that reducing the PWG exerts substantial effects on children's socio-emotional skills. Point estimates are close to zero and cannot be statistically distinguished from zero except for the case of extraversion. However, as previously, statistical significance also vanishes for this outcome once the FWER of the seven tested hypotheses is accounted for. Furthermore, the robustness analyses in section 4.3 show that the positive significant effect on extraversion is susceptible to alternative variable definitions, control variables, and sample restrictions (Appendix Table S.14).

Contextualizing effect sizes. Whether these null effects are informative depends on the study design's ability to rule out meaningful effect sizes. I assess this question in two steps. First, I calculate minimum detectable effect (MDE) sizes at 80% power. Appendix Figure S.10 shows the results of these power calculations: MDEs at sample sizes of $2,000$, $4,000$, and $6,000$ observations are 0.22, 0.16, and 0.13 SD, respectively. To put these MDEs into perspective, a recent overview article by Schurer (2017) assesses the impact of various educational interventions on different measures of socio-emotional skills. Absolute effect sizes range between zero and 0.7 SD. Furthermore, 26 out of the 34 estimates are larger than 0.1 SD. This pattern suggests that my study design is well-powered to detect the existence of prevalent effect sizes that have been established in the current literature on socio-emotional skills.

Second, I perform a back-of-the-envelope calculation of how the estimates translate into later-life earnings. In particular, I multiply the 95% confidence intervals of my estimates with the corresponding effects of Big Five personality traits and externalizing/internalizing behavior on annual earnings at age 50 as estimated in Papageorge et al. (2019). Figure 3 shows that the range of implied earnings changes is small. For conscientiousness, extraversion, agreeableness, neu-

FIGURE 3 – Implied effects on earnings in comparison to other interventions



Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows the implied effects of changes in children's socio-emotional skills on annual earnings at age 50. Point estimates for a 10% decrease in the PWG and associated 95% confidence intervals are taken from Table 4. Effect sizes for other interventions are taken from the studies listed in the legend. All data points are multiplied with the effect sizes for 1 SD increases in socio-emotional skills on log-weekly earnings (Papageorge et al., 2019, Column 3 of Table D.11): 0.067 (Openness), 0.023 (Conscientiousness), 0.024 (Extraversion), -0.032 (Agreeableness), -0.027 (Neuroticism), 0.017 (Externalizing behavior), -0.049 (Internalizing behavior).

roticism, and internalizing/externalizing behavior, I can exclude earnings increases/decreases larger than 1% per year. The credible effect range for openness is only marginally larger. To put these implied earnings effects into perspective, I again compare them to those of other interventions analyzed in the existing literature. For example, in a recent paper, Fort et al. (2020) show that a substitution from family care to public daycare in Bologna significantly decreases the openness and agreeableness of the affected children. The implied earnings effect of their estimates correspond to earnings changes of -2.8% (openness) and 1.3% (agreeableness) per year. These implied effect sizes can be comfortably ruled out for a 10% decrease in the PWG in Germany. While these back-of-the-envelope calculations arguably rely on strong assumptions, they support the conclusion that equalizing labor market incentives between mothers and fathers does not lead to changes in children's socio-emotional skills that are large enough to have meaningful consequences for their long-term life outcomes.[22]

Long-run analysis. The previous discussion considered the short-term effect of the PWG on children's socio-emotional skills. However, it could be the case that small short-run effects accumulate over time into sizable long-run effects. The potential for such a pattern is highlighted by Appendix Table S.3, where I use value-added models to show that socio-emotional skills of children are self-productive. To investigate the possibility of long-run effects, I modify the baseline estimation as follows: I fix the PWG at child age two. Then, I use split sample analyses to estimate the effect of the early-life PWG on children's socio-emotional skills at ages 3, 6, and 10.[23] If it was the case that small short-run effects accumulate over time, we should see increasing effect sizes as children grow up.

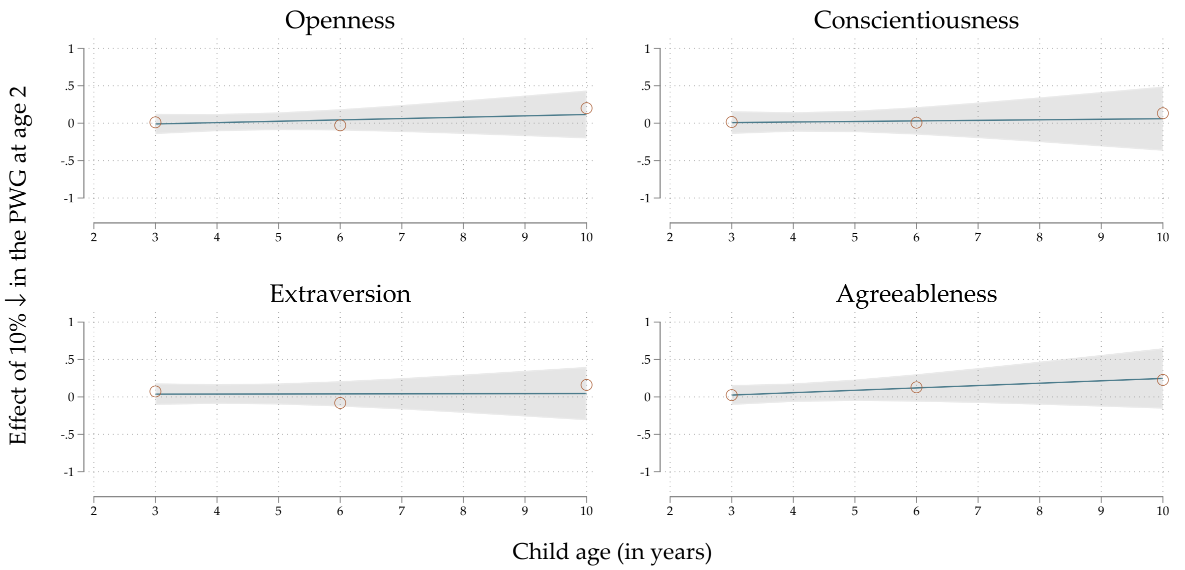
Figure 4 suggests that this is not the case and that the null effects persist in the long run. The effect sizes for the early-life PWG on children's Big Five personality traits are always close to zero and frequently change signs as children grow up. Therefore, the gradients for predicted effects across the considered age range are flat and do not point to an increasing importance of early-life PWGs for children's socio-emotional skills until age 10.

Furthermore, in Table 5, I show that the PWG at age 2 does not affect other outcomes related to children's socio-emotional skills and long-term life outcomes.

[22] A core assumption for this exercise is that the short-run changes in socio-emotional skills from Table 4 persist into adulthood. This assumption is supported by Figure 4, where I show that effects remain near zero over until age 10. Furthermore, I have to assume that the effect sizes of Papageorge et al. (2019) are causally identified and externally valid for other cohorts and countries.

[23] I omit neuroticism, externalizing/internalizing behaviors as data on these skills is only available for two ages.

FIGURE 4 – Long-term effects of the PWG at age 2 on children's socio-emotional skills



Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows long-term changes in children's socio-emotional skills in response to a 10% decrease of the PWG at child age 2. The circles indicate treatment effects for children's socio-emotional skills measured at ages 3, 6, and 10 based on split sample analyses. The solid lines indicate linear predictions across the age range 3-10. The gray shaded areas mark 95% confidence intervals. All regressions control for family fixed effects, and the sum of maternal and paternal wages. Standard errors are clustered at the family level.

First, I consider children's BMI at age 6 as a proxy for their health. Existing literature suggests that personality and externalizing/internalizing behaviors correlate strongly with the BMI (Attanasio et al., 2020a; Conti and Hansman, 2013). Furthermore, early-life health is an important determinant of the long-term life outcomes of individuals (Conti et al., 2010).[24] In this analysis, I classify children as underweight (overweight) if their BMI is below (above) the 10th (90th) percentile of the age-specific BMI distribution in Germany (Schaffrath Rosario et al., 2010). Column 1 of Table 5 shows that we cannot reject the null hypothesis that the PWG has no impact on whether children are underweight or overweight.

Second, I consider the age of school entry as another proxy for developmental problems of the child. In Germany, all children complete a compulsory school readiness examination the year before their scheduled school entry. These examinations are conducted by pediatricians who assess children's language, motor, and socio-emotional skills (Cornelissen et al., 2018; Felfe and Lalive, 2018). Children's school entry may be delayed if they perform poorly in the school readiness examination. Therefore, I construct an indicator for whether children entered school

[24] In Appendix Table S.15, I show that children's socio-emotional skills predict children's BMI and other outcomes in my sample as well, even conditional on a rich set of controls.

Table 5 – Long-term effects of PWG at age 2 on other child outcomes

	BMI at age 6: Under/Overweight (yes/no) (1)	Delayed school entry (yes/no) (2)	Upper secondary school track (yes/no) (3)
Effect of 10% ↑ in parental wages at age 2			
Mother	0.051 (0.167)	-0.221 (0.139)	0.021 (0.069)
Father	0.052 (0.060)	0.006 (0.026)	0.048 (0.036)
Panel (b): Effect of 10% ↓ in PWG at age 2			
PWG	-0.001 (0.088)	-0.113 (0.071)	-0.013 (0.041)
Family FE	✓	✓	✓
Year FE	✓	✓	✓
N	2,678	2,077	2,710
R^2	0.500	0.558	0.738
Outcome Mean	0.379	0.094	0.503
Outcome SD	0.485	0.292	0.500

Data: GSOEP.
Note: Own calculations. This table shows long-term changes in other child outcomes in response to changes in maternal and paternal potential wages. All regressions control for family and year fixed effects. All regressions control for family times child age fixed effects and year fixed effects. Regressions in Panel (b) also control for the sum of maternal and paternal potential wages. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

after their scheduled school starting age which is typically at age 6. Column 3 of Table 5 shows that the PWG does not impact children's age of school entry.

Lastly, I consider whether children attend the high academic track in secondary school. In Germany, children transition to secondary school at ages 10–12 depending on the federal state. They are tracked based on teacher grades and teacher recommendations, both of which are likely influenced by student's socio-emotional skills (e.g., Jackson, 2019; Sorrenti et al., forthcoming). Furthermore, this tracking decision has important long-run implications since only the high academic track leads to a school-leaving certificate that grants access to university. Column 4 of Table 5 shows that the PWG does not influence whether children attend the high academic track in secondary school track or not.

In summary, these analyses support the conjecture that PWG changes do not have significant consequences for children's socio-emotional skills and long-term life outcomes.

4.3 *Robustness*

Alternative construction of potential wages. In Panel (a) of Appendix Table S.14, I show the robustness of my findings to alternative ways of constructing potential wages.

First, in the baseline, I impute daily wages above the social security contribution limit by wage draws from a truncated log-normal distribution (Dustmann et al., 2009; Gartner, 2005). Results remain unaffected when (i) using censored wages without any imputation, or (ii) uniformly replacing censored wages with 150% of the social security contribution cap—an imputation technique commonly employed for top coded incomes in the Current Population Survey (CPS, Autor et al., 2008; Shenhav, 2021).

Second, in the baseline, I calculate sector shares for the base year 1995 and keep them fixed over time. My results remain unaffected when (i) allowing for an updating term that accounts for intra-industry shifts in the occupation structure (Shenhav, 2021), or (ii) using floating sector shares evaluated at $t - 10$, e.g., using $\hat{w}_{g,2017} = \sum_s \frac{E^s_{g,2007}}{E_{g,2007}} w^s_{2017}$ instead of $\hat{w}_{g,2017} = \sum_s \frac{E^s_{g,1995}}{E_{g,1995}} w^s_{2017}$.

Lastly, one may be concerned that misreports in working hours lead to measurement error in parent's potential wages (e.g., Borjas and Hamermesh, 2024). To assuage this concern, I repeat the analysis using potential daily wages that are based on administrative wage data from the SIAB only. These data are less prone to measurement error since they are the legal basis for employer's social security contributions. Results remain unaffected by this change suggesting limited scope for misreported working hours to bias my estimates.

Alternative control variables. In Panel (b) of Appendix Table S.14, I show the robustness of my findings to alternative specifications of X'_{it}.

First, in the baseline, I control for family times child age fixed effects $\gamma_{f(i)a(it)}$ and time fixed effects τ_t (as well as $\hat{w}^{\Sigma}_{it-1}$ when estimating effects of the PWG). My results remain unaffected when expanding X'_{it} by measures for the child's birth rank, biological sex, month of birth, and the number of children in the household. This result highlights the orthogonality of wage shocks to intra-family variation in sibling and family characteristics after conditioning on $\gamma_{f(i)a(it)}$ and τ_t (see also Table 2).

Second, my identification strategy assumes that group-specific sector shares in the base year 1995 do not correlate with other factors that predict intra-family changes in the outcomes of interest. To support the validity of this assumption, I show that results remain unaffected when allowing for (i) time trends by CZ and (ii) time trends by the education level of the highest-educated parent. These results also rule out concerns about sorting into local labor markets and the selective acquisition of education across the period of the sibling comparison.

Lastly, the expansion of publicly subsidized childcare in Germany was characterized by strong regional heterogeneity. Such heterogeneity would undermine the identification assumption if intra-family variation in potential wages correlated with changes in the availability and quality of public childcare slots. To address this concern, I show that results remain unchanged when adding controls for (i) the CZ- and year-specific ratio of enrolled children to available slots and (ii) the CZ- and year-specific ratio of enrolled children to pedagogical personnel.[25]

Alternative sample restrictions. In Panel (c) of Appendix Table S.14, I show the robustness of my findings to alternative sample restrictions.

First, my baseline estimates are derived from a sample of intact families where I allow non-biological parent-child relationships and non-married parental couples. My results remain unaffected when restricting the sample to (i) biological parents or (ii) married parents.

Second, my empirical strategy is based on a sibling fixed effects model and excludes single children from the analysis. To accommodate single children, I change my identification strategy to a within-child estimation. The sample for this analysis differs from my core analysis sample in two ways. On the one hand, it includes single children without siblings. On the other hand, it excludes children for which I do not have multiple observations over time. In particular, I follow Agostinelli and Sorrenti (2018) and Dahl and Lochner (2012) and estimate a first-difference model using child-specific outcomes and parental potential wages at ages 3, 6, and 10. I include non-parametric controls for year, child age, sex, CZ of residence, and education level of the highest educated parent. Thereby, I effectively allow for differential trends in child outcomes by observable characteristics. Results are again similar to my baseline esti-

[25]Demand for public childcare strongly exceeds supply. Therefore, actual enrollment is a suitable proxy for the availability of childcare slots (Felfe and Lalive, 2018).

mates except for a significant decrease in internalizing behavior at the 10%-level. Since this is the only specification where I find an effect of the PWG on internalizing behavior, this finding does not overturn the central conclusion that changes in the PWG do not affect children's socio-emotional skills in a meaningful way. The similarity of results between the sibling fixed effects model and the within-child estimation also addresses concerns that null effects in the siblings model are driven by attenuation bias due to sibling spillovers.

Alternative standard errors. In Appendix Table S.16, I show the robustness of my statistical inferences to alternative ways of calculating standard errors. In my baseline analysis, I cluster standard errors at the family level, i.e., I allow for correlation of error terms across children from the same parents over time. However, alternative levels of clustering are conceivable. Therefore, I follow MacKinnon et al. (2023) and test for the equality of the error variance matrix of my baseline estimates with estimates that assume alternative levels of clustering. Results show we can reject the null hypothesis of equality when comparing the error variance matrix without clustering to the error variance matrix with clustering at the family level. This result shows that standard errors need to be clustered. However, comparing family-level clustering to clustering by (i) maternal education times paternal education times CZ cells, (ii) maternal education cells, (iii) paternal education cells, or (iii) CZ cells, we cannot reject the null in the overwhelming majority of cases at conventional levels of statistical significance. In sum, these results suggest that the baseline level of clustering is appropriate and that I am unlikely to over-reject (under-reject) null hypotheses based on optimistic (pessimistic) standard errors.

Furthermore, I assess the impact of measurement error in the dependent variable on my results. Measures of children's socio-emotional skills are based on maternal reports and may be prone to measurement error. While measurement error in the dependent variable does not bias point estimates, it may inflate standard errors. Therefore, I outline a measurement error correction procedure and provide estimates of confidence intervals under credible assumptions about the extent of measurement error in children's socio-emotional skills (Appendix C). The results of this exercise show that the null effects in Table 4 persist even after correcting for measurement error in the outcomes of interest.

4.4 Mechanisms

Parental investments. The previous sections have shown that changes in the labor market incentives of mothers and fathers lead to important changes in parents' time allocations. However, these changes do not affect children's socio-emotional skills. To understand this null finding, I investigate the impact of changes in the PWG on the time investments (total parental care, use of formal/informal care) and monetary investments of parents (disposable family income, share of resources controlled by mothers).

The choice of these investment indicators is motivated by existing literature. In terms of time investments, existing literature shows that non-parental care, and especially informal care, is an imperfect substitute for maternal care at home. Therefore, a substitution from maternal (informal) to informal (maternal) care is likely to exert a negative (positive) effect on children's development (Bernal and Keane, 2011; Datta Gupta and Simonsen, 2010; Duncan et al., 2023). In terms of monetary investments, existing literature shows that financial resources promote child development by allowing families to purchase child-centered goods and by reducing parental stress (Agostinelli and Sorrenti, 2018; Akee et al., 2018; Dahl and Lochner, 2012; Løken et al., 2012; Nicoletti et al., 2023). Furthermore, mothers have a higher propensity to use available financial resources to benefit their children (Duflo, 2012; Lundberg et al., 1997). Therefore, increases (decreases) in the disposable income of families and the increased (decreased) share of resources controlled by mothers are likely to exert a positive (negative) effect on children's development. These findings from the existing literature are also corroborated by corresponding analyses on the GSOEP, showing that parental care, family income, and the maternal earnings share are positively associated with children's socio-emotional skills, whereas the effect of informal care is negative (Appendix Table S.19).

The upper panel of Table 6 displays the effects of maternal and paternal potential wages on parental investments.

Changes in maternal potential wages stimulate opposing forces on parents' time and monetary investments. A 10% increase in maternal potential wages neither affects the total care parents provide to their children (Column 1) nor the probability of children enrolling in formal child-

Table 6 – Parental wages and parental investments

	Time investments			Monetary investments	
	Parental care (hours/day) (1)	Formal care (yes/no) (2)	Informal care (yes/no) (3)	Total disp. family income (in Thsd. €) (4)	Share maternal earnings (in %) (5)
Panel (a): Effect of 10% ↑ in parental wages					
Mother	0.110	0.005	0.089*	3.785**	9.151**
	(0.500)	(0.043)	(0.049)	(1.684)	(4.172)
Father	0.574*	-0.031*	-0.085**	-0.584	-4.017***
	(0.334)	(0.016)	(0.033)	(0.488)	(1.495)
Panel (b): Effect of 10% ↓ in PWG					
PWG	-0.232	0.018	0.087***	2.185**	6.584***
	(0.298)	(0.024)	(0.030)	(0.882)	(2.287)
Family × child age FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	5,484	5,484	5,484	5,484	5,484
R^2	0.751	0.793	0.723	0.921	0.803
Outcome Mean	9.894	0.656	0.294	46.019	19.200
Outcome SD	5.197	0.475	0.456	25.994	22.988

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to changes in maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects. Regressions in Panel (b) also control for the sum of maternal and paternal potential wages. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

care (Column 2). However, it increases the probability that children are enrolled in informal childcare by 0.09 points (Column 3). This pattern echoes that mothers protect their overall time with children by increasing their childcare engagement after work (see the discussion above). It also suggests that families substitute in-home care with informal childcare arrangements while mothers work.[26] The labor supply responses of mothers also have substantial effects on the availability of monetary resources within households: a 10% increase in maternal potential wages increases total disposable family income by 3.78 Thsd. € (Column 4) and also increases the maternal share of earnings by 9.15 percentage points (Column 5).

[26]In Appendix Table S.17, I decompose the effect on informal childcare into the use of different providers: non-resident extended family, friends, and paid in-home babysitter. All effects are qualitatively similar, however, the strongest increases are observed for using the non-resident extended family. In Appendix Table S.18, I also analyze changes at the intensive margin. The sample for this analysis is smaller, the information comes from different questionnaires, and the definitions of informal and formal care differ to the baseline. For example, in this analysis informal care also includes resident family members such as older siblings and grandparents. Despite these caveats, the results on the extensive margin are similar to the baseline analysis shown in Table 6. Furthermore, the results do not suggest changes at the intensive margin.

The effects of paternal potential wages on parental investments are also ambiguous. A 10% increase in paternal potential wages increases the total amount of time parents devote to childcare by 0.57 hours per day (Column 1). This increase is predominantly driven by mothers who withdraw from the labor market and increase their provision of in-home childcare (see Table 3). While there are no effects on the probability of being enrolled in formal childcare (Column 2), the probability of using informal childcare decreases by 0.08 points (Column 3). Hence, increases in paternal wages lead families to substitute away from informal childcare to in-home care by mothers. Furthermore, increases in paternal potential wages do not affect total disposable family income (Column 4). This null effect arises because fathers' increased income is offset by mothers' decreased labor market activity (see Table 3). However, the increased earnings of fathers and decreased earnings of mothers lead to a 4.02 percentage points decline in the share of resources controlled by mothers (Column 5).

Finally, the lower panel of Table 6 displays the effects of a 10% decline in the PWG on parental investments. Again, I control the sum of maternal and paternal wages in all regressions to isolate the effect of relative earnings potentials from the effects of wage levels. Consistent with the individual effects of maternal and paternal wages, a 10% decrease in the PWG increases the probability of using informal childcare by 0.09 points (Column 3), increases disposable household income by 2.18 Thsd. € per year (Column 4), and increases the total share of resources controlled by mothers by 6.58 percentage points (Column 5).

In sum, these findings suggest that decreases in the PWG trigger adverse effects on parental time investments that are compensated by positive effects in terms of monetary investments. In Appendix Table S.20, I show the robustness of these effects concerning alternative constructions of potential wages, alternative specifications of X'_{it}, and alternative sample restrictions. Tests for the appropriate level of clustering are shown in Appendix Table S.16.

Heterogeneity analysis. The average effects presented thus far may mask substantial heterogeneity. On the one hand, children may differ in how they react to a given change in parental investments. On the other hand, families may differ in how strongly parental investments adjust to changes in the PWG. Therefore, I consider six heterogeneity dimensions: child sex (Baker and Milligan, 2016; Bertrand and Pan, 2013), birth order (Black et al., 2018), child age (Del Boca et al., 2017; Heckman and Mosso, 2014), regional differences between East and West Germany (Boelmann et al., forthcoming; Lippmann et al., 2020), maternal education (Agostinelli and Sorrenti, 2018; Carneiro et al., 2013), and poverty status (Akee et al., 2013; Løken et al., 2012).

To strengthen statistical power and to alleviate concerns about multiple hypothesis testing, I conduct heterogeneity analyses for two summary indexes: a "personality factor," which is the first factor from a factor analysis using all items underlying the Big Five questionnaire, and a "total difficulty score" which is the first factor from a factor analysis using all items underlying the externalizing and internalizing behavior sub-scales of the SDQ. Factor analyses are run separately by age bins (2–3, 5–6, and 9–10). The resulting factors are standardized by child sex and age to account for gender- and age-specific differences in socio-emotional skills.[27]

Table 7 presents the results for a 10% decrease in the PWG on children's socio-emotional skills for different population subgroups. In general, there is limited evidence for heterogeneous treatment effects of the PWG: there are no detectable differences by child sex, birth order, maternal education, and poverty status.

However, there is evidence that the personalities of children above the age of 6 are more negatively affected by closing PWGs: a 10% decrease in the PWG decreases the personality factor of older children ($>$ 6 years) by 0.21 SD more than of younger children ($\leq$ 6 years). We can link this finding back to the heterogeneous effects of the PWG on parental investments.[28] Appendix Table S.24 shows that older children (i) are more likely exposed to informal childcare, and (ii) their households experience a smaller increase in disposable income. These patterns can be explained by the lower availability of afternoon care in primary schools compared to center-based child care for preschool children. Furthermore, parents' labor supply may be less responsive to wage incentives as many have transitioned back to their desired long-term levels of labor market activity by the time their children attend school (Goldin et al., forthcoming). In line with our previous interpretation of parental investments, this pattern suggests that the

[27] Appendix Table S.21 shows that the "personality factor" relates positively to openness, conscientiousness, extraversion, agreeableness, and negatively to neuroticism. The "total difficulty score" relates positively to externalizing/internalizing behavior. In conjunction with the positive (negative) effects of openness, conscientiousness, extraversion, agreeableness (neuroticism, externalizing, internalizing behaviors) on child outcomes (Appendix Table S.15), these loadings suggest that the "personality factor" ("total difficulty score") is a summary index for positive (negative) tendencies in children's socio-emotional skills.

[28] See Appendix Tables S.22–S.27 for heterogeneity analyses on parental investments.

TABLE 7 – Heterogeneity: Effect of 10% ↓ in the PWG on children's socio-emotional skills by subgroup

Panel (a): Effect of 10% ↓ in PWG on Personality Factor

Child sex			Birth order			Child age		
Male	Female	Diff.	First	Higher	Diff.	≤ 6	> 6	Diff.
-0.007	0.016	0.023	0.004	0.004	0.001	0.055	-0.157	-0.212*
(0.066)	(0.065)	(0.025)	(0.064)	(0.065)	(0.022)	(0.067)	(0.115)	(0.122)
Region of residence			**Education (Mother)**			**At risk of poverty**		
West	East	Diff.	Low	High	Diff.	No	Yes	Diff.
0.023	-0.022	-0.044	-0.130	0.026	0.157	0.019	0.055	0.036
(0.079)	(0.120)	(0.151)	(0.113)	(0.084)	(0.119)	(0.066)	(0.084)	(0.061)

Panel (b): Effect of 10% ↓ in PWG on Total Difficulty Score

Child sex			Birth order			Child age		
Male	Female	Diff.	First	Higher	Diff.	≤ 6	> 6	Diff.
0.099	0.118	0.019	0.111	0.111	-0.000	0.097	0.167	0.070
(0.094)	(0.096)	(0.037)	(0.092)	(0.096)	(0.033)	(0.093)	(0.194)	(0.186)
Region of residence			**Education (Mother)**			**At risk of poverty**		
West	East	Diff.	Low	High	Diff.	No	Yes	Diff.
0.261***	-0.060	-0.321***	0.069	-0.050	-0.118	0.093	0.141	0.048
(0.088)	(0.099)	(0.111)	(0.164)	(0.124)	(0.134)	(0.097)	(0.126)	(0.073)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in children's socio-emotional skills in response to a 10% decrease in the PWG for different population subgroups. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

negative effect of increased informal childcare is less counterbalanced by increased financial resources, leading to more negative effects of the PWG on the socio-emotional development of older children.

In addition, there is evidence that the closing PWG leads to higher levels of behavioral problems in West Germany than in East Germany: a 10% decrease in the PWG increases the total difficulty score of children in the West by 0.32 SD more than of children in the East. This finding is again consistent with parental investment patterns. Appendix Table S.25 shows that parents in the West react to decreases in the PWG with a higher likelihood of using informal childcare arrangements, echoing the lower availability of center-based childcare in the West than in the East. At the same time, the increased exposure to informal care is not compensated by increases in household income or the maternal income share, leading to a more negative effect of the PWG on the socio-emotional development of children in West Germany.

In summary, these results suggest that the small average effects of the PWG on children's socio-emotional skills are not an artifact of masked heterogeneity. However, they also illustrate that children's socio-emotional development may be adversely affected if households cannot compensate their children for decreased time investments with increased monetary investments (or vice versa).

5 CONCLUSION

In this paper, I study how changes in the relative pay gap of mothers and fathers affect the skill development of their children.

Drawing on survey and administrative data from Germany, I combine a within-family sibling comparison with a shift-share design to estimate the causal effects of the PWG on children's socio-emotional development and the monetary and time investments provided by parents.

I find that changes in the PWG do not affect children's socio-emotional skills. These null effects are estimated precisely enough to imply modest earnings effects in the future and to exclude the effect sizes of various interventions analyzed in the existing literature. Furthermore, these findings can be rationalized by the offsetting impact on the time and monetary investments that parents provide to their children. While increases in the PWG lead to increases in children's exposure to informal care, they also lead to increases in the disposable income of households and the share of financial resources controlled by mothers.

Fostering gender equality and promoting the development of children are important goals of public policy. However, these goals are often thought to conflict with each other.[29] In contrast to such concerns, the evidence presented in this study suggests that strides toward gender equality do not imply adverse effects on the skill development of the next generation.

[29] For example, the former Vice President of the US, Michael Pence, once warned of children's "stunted emotional growth" if two parents work. Even today, most Americans say children are better off with one parent at home (Graf, 2016).

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The Parental Wage Gap and the Development of Socio-emotional Skills in Children

Paul Hufe

Supplementary Material for Online Publication
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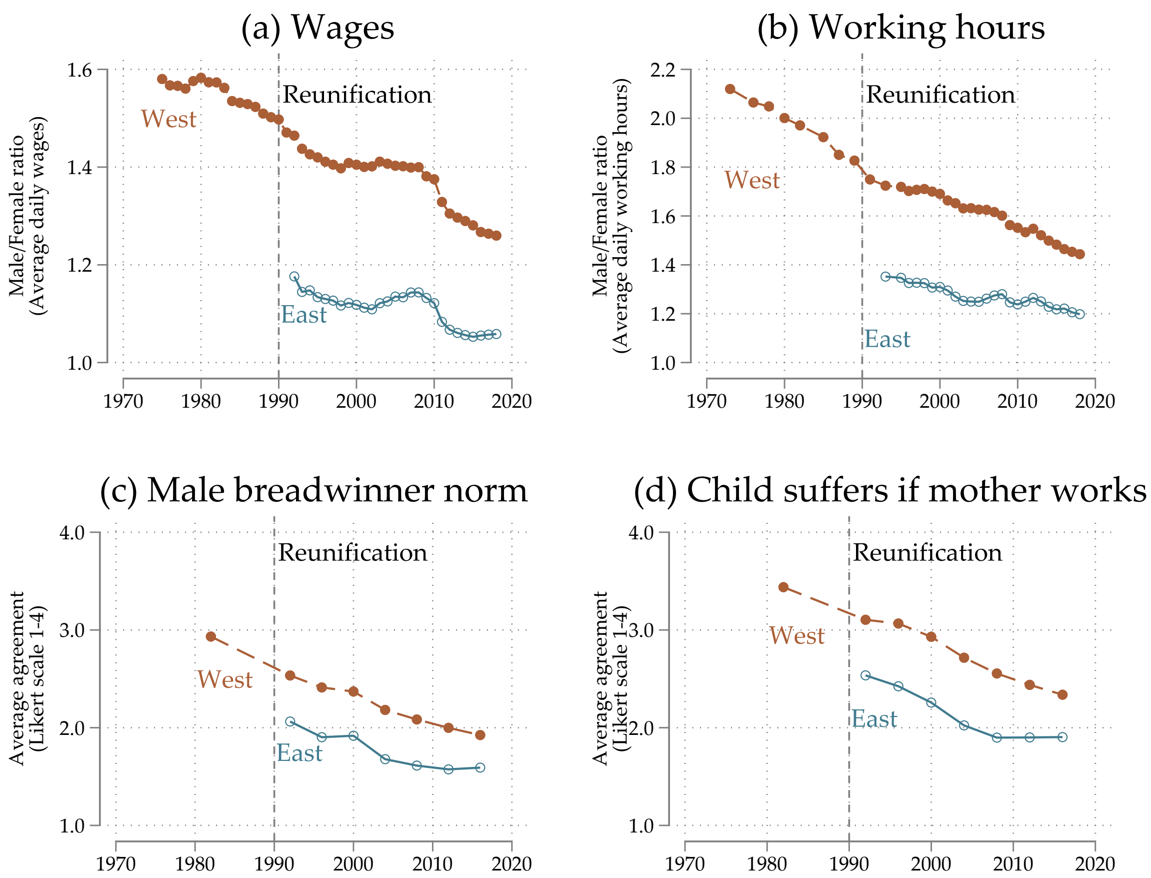
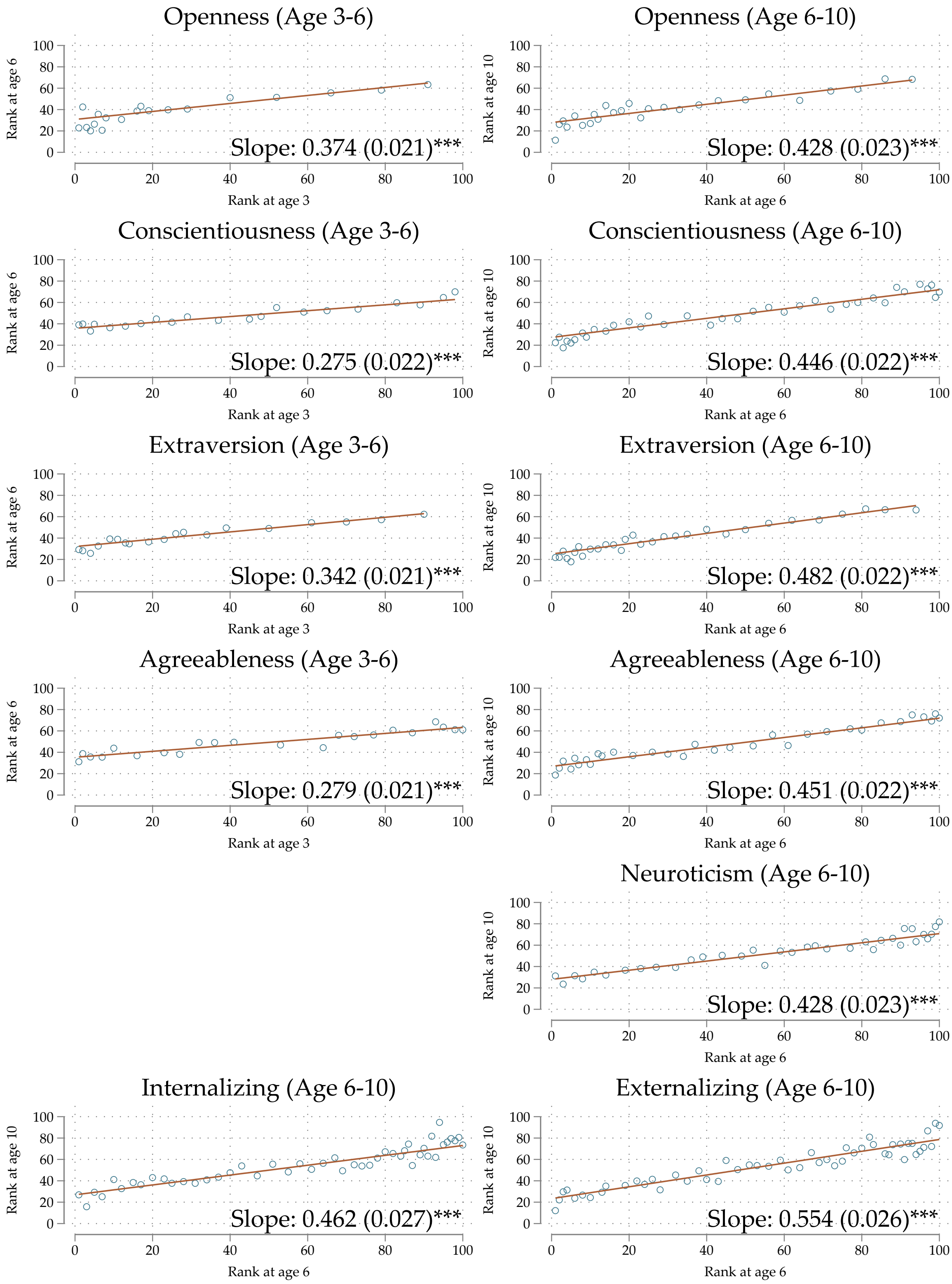
A ADDITIONAL FIGURES

FIGURE S.1 – Gender gaps and gender role attitudes in Germany by region, 1973–2019



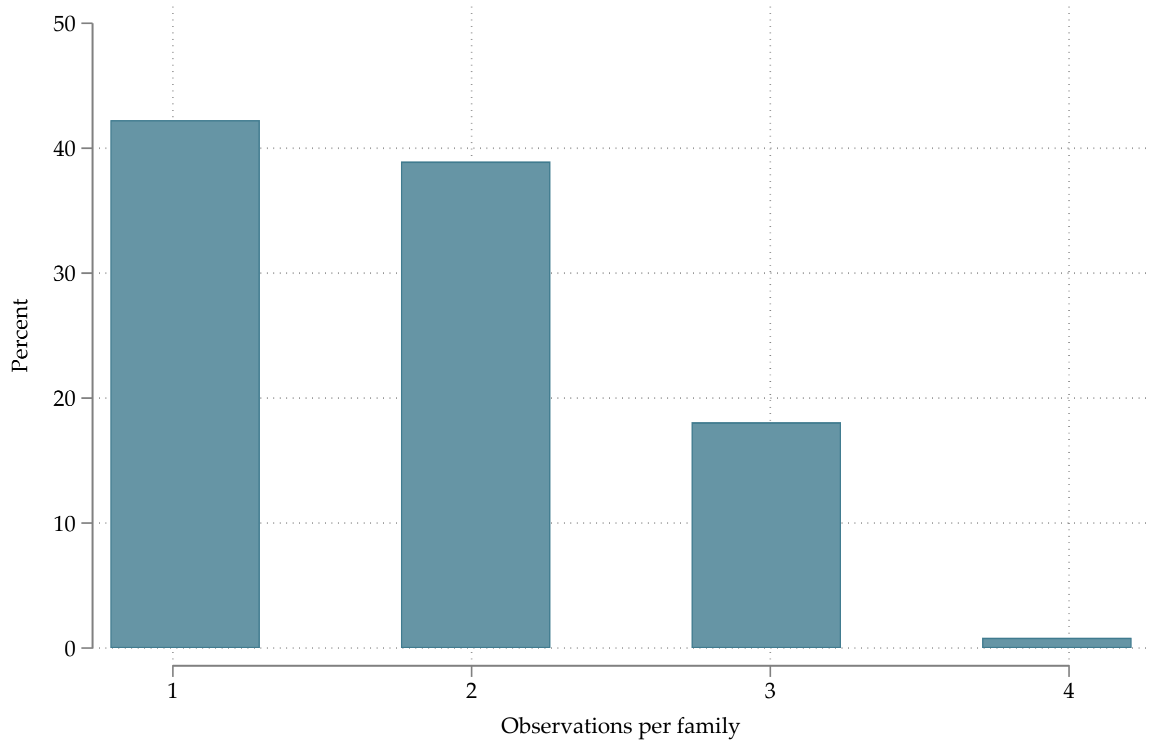
Data: SIAB, MZ, ALLBUS.
Note: Own calculations. Panel (a) shows the male-to-female ratio in mean daily wages from 1975 to 2019. Daily wages are calculated for all SIAB observations aged 18–63 that are subject to social security contributions. Panel (b) shows the male-to-female ratio in daily working hours from 1973 to 2019. Daily working hours are calculated for all MZ observations aged 18–63 by dividing their working hours in a typical work week by five. Panel (c) and (d) show the average agreement of ALLBUS respondents aged 18–63 to the following statements: (c) It is much better for everyone concerned if the man goes out to work and the woman stays at home and looks after the house and children; (d) A small child is bound to suffer if his or her mother goes out to work.

FIGURE S.2 – Rank stability of children's socio-emotional skills



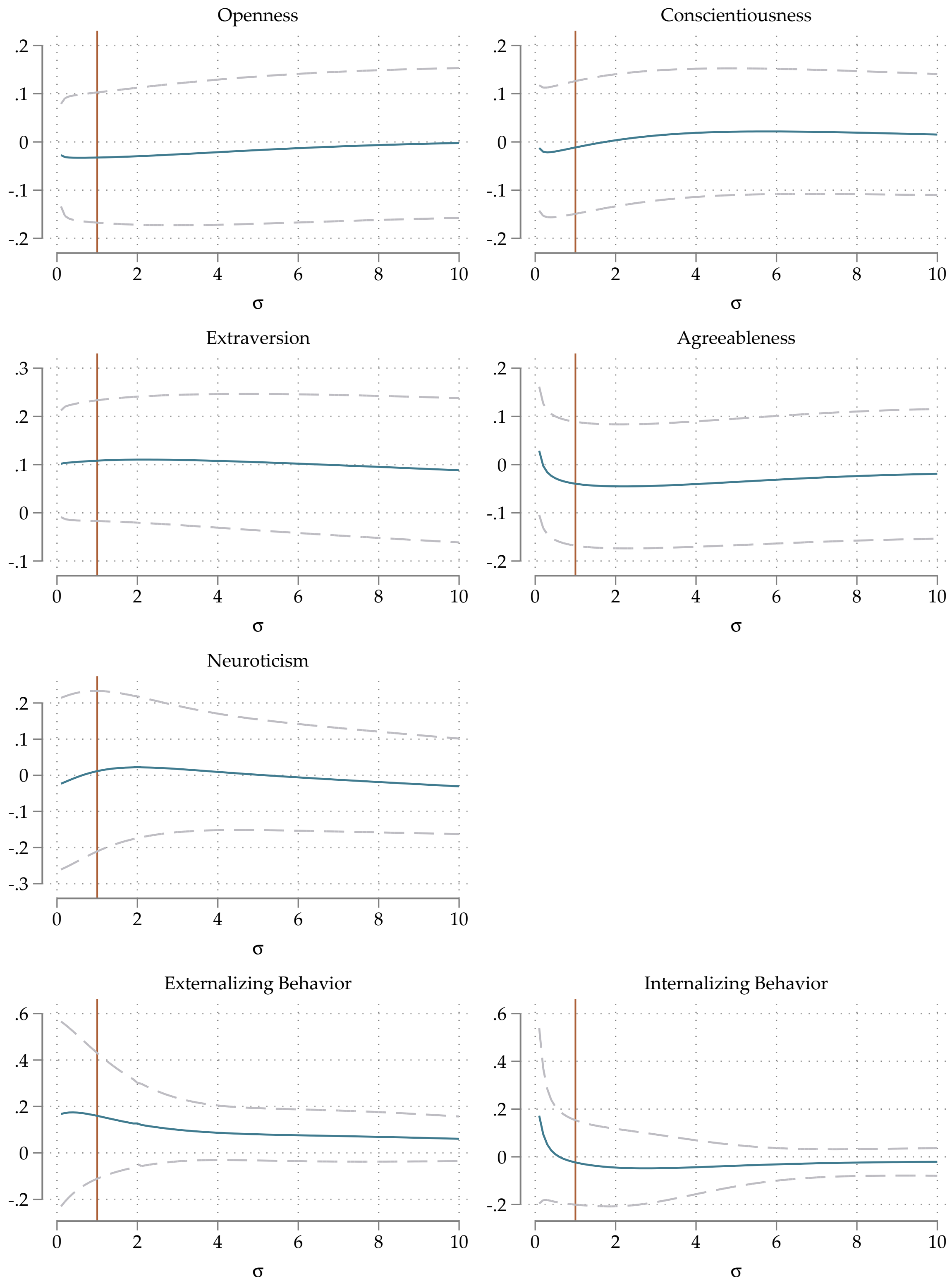
Data: GSOEP, SIAB, MZ.
Note: Own calculations. This graph shows rank-rank correlations of children's socio-emotional skills at different ages. This sample differs from the core analysis sample: I do not restrict the sample to the availability of corresponding sibling and parental investment data. Furthermore, the sample is restricted to children with observations in socio-emotional skills at ages 3/6 and 6/10, respectively. Standard errors (in parentheses) are heteroskedasticity-robust. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

FIGURE S.3 – Repeated family observations



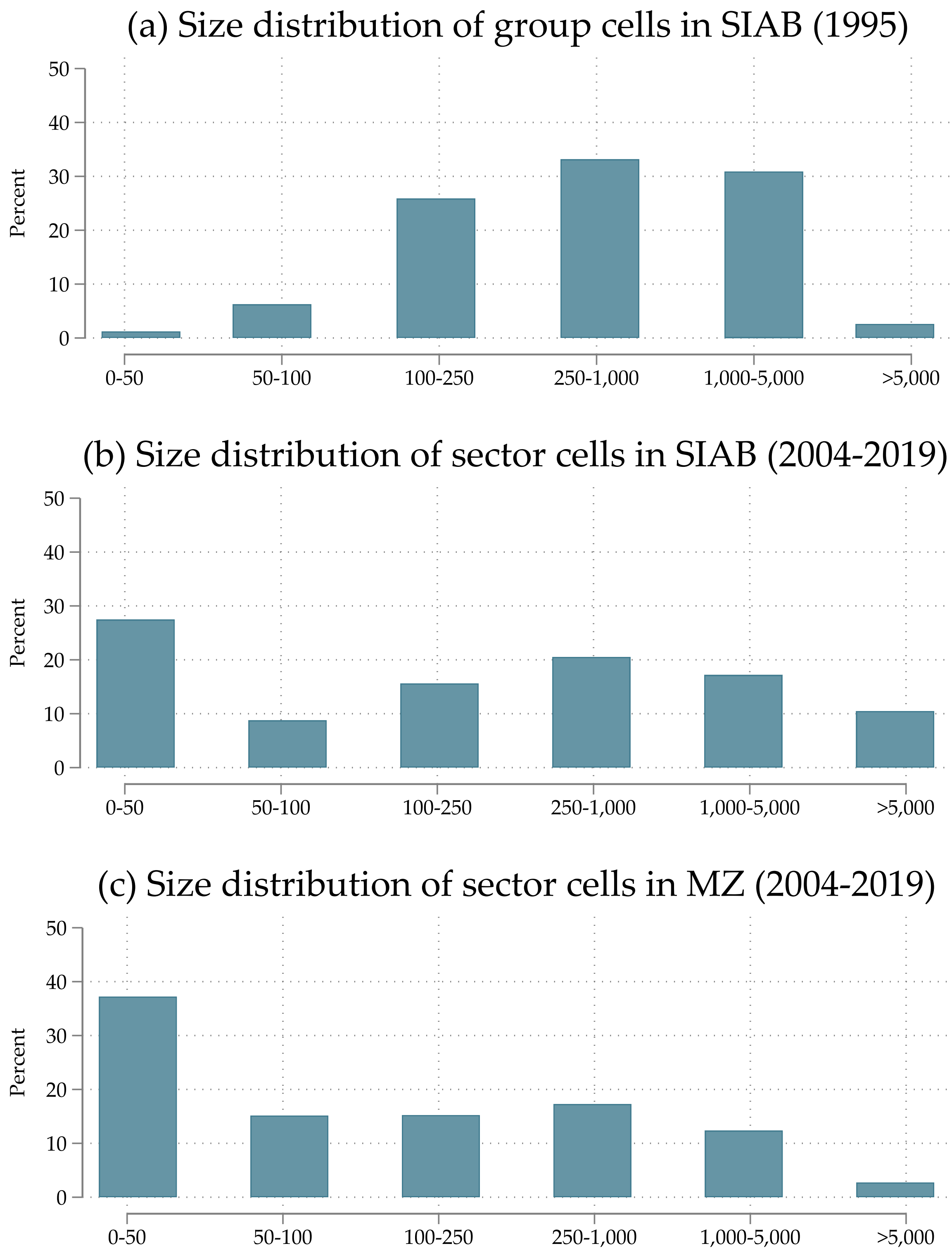
Data: GSOEP.
Note: Own calculations. This figure shows the frequency of repeated parent-child observations in the core sample described in Table 1.

FIGURE S.4 – Robustness to monotonic transformations of outcome variable



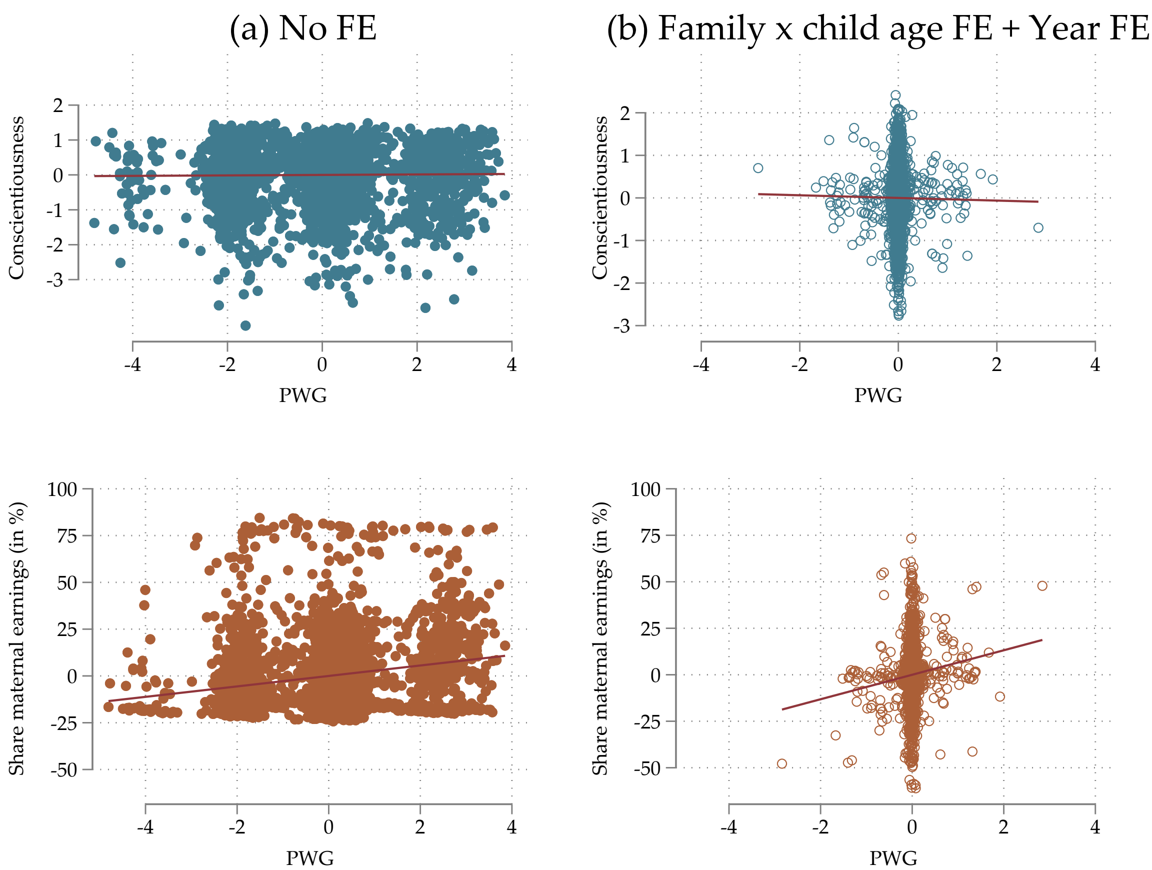
Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows standardized treatment effects of a 10% decrease in the PWG using monotonic transformations of children's socio-emotional skills. Outcomes are transformed as follows: $f(y) = y^{\sigma}$, where σ is taken over the interval [0.1(0.1)10]. Vertical lines show the baseline estimate with $\sigma = 1$ (see equation 4). Dashed lines show the corresponding 95% confidence intervals; standard errors are clustered at the family level. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1.

FIGURE S.5 – Cell sizes for construction of potential wages



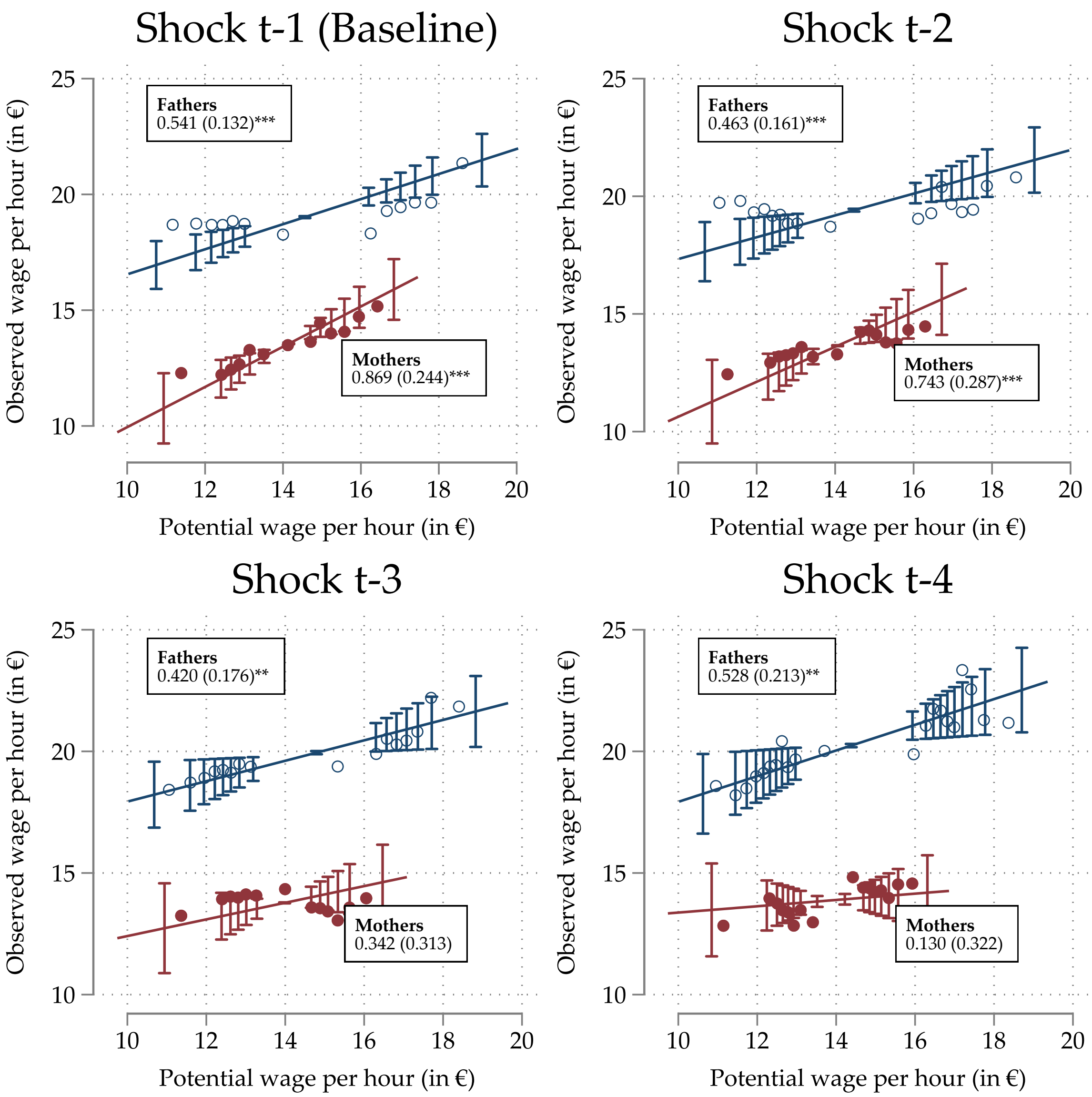
Data: SIAB, MZ.
Note: Own calculations. This figure shows the distribution of cell sizes for the construction of potential wages. Panel (a) refers to cells of groups g in base year 1995 (Term [1] of equation 1). Panel (b) refers to cells of sectors s in the years 2004-2019 used for measuring daily wages (Term [2] of equation 1). Panel (c) refers to cells of sectors s in the years 2004-2019 used for measuring daily working hours (Term [2] of equation 1).

FIGURE S.6 – Graphical display of identifying variation



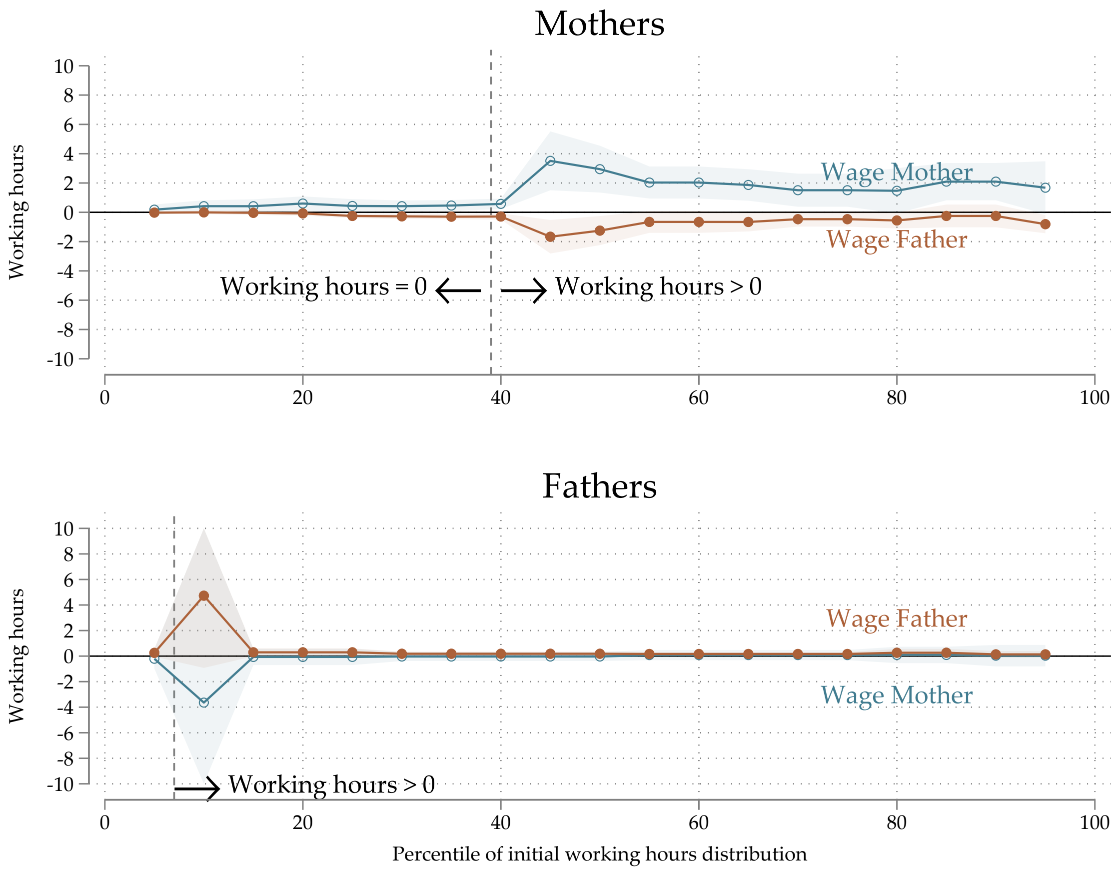
Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows raw data for the relationships of at 10% decrease in the PWG with children's openness and the share of maternal earnings, respectively. Panel (a) shows data after controlling for the sum of maternal and paternal potential wages. Panel (b) shows data after additionally controlling for family times child age fixed effects and year fixed effects. Solid lines show the linear best fit. 388 observations have a constant PWG within child age fixed effect groups. These observations do not contribute to the identification. All coefficients are estimated on the core sample described in Table 1.

FIGURE S.7 – Within-person correlation of potential and observed wages



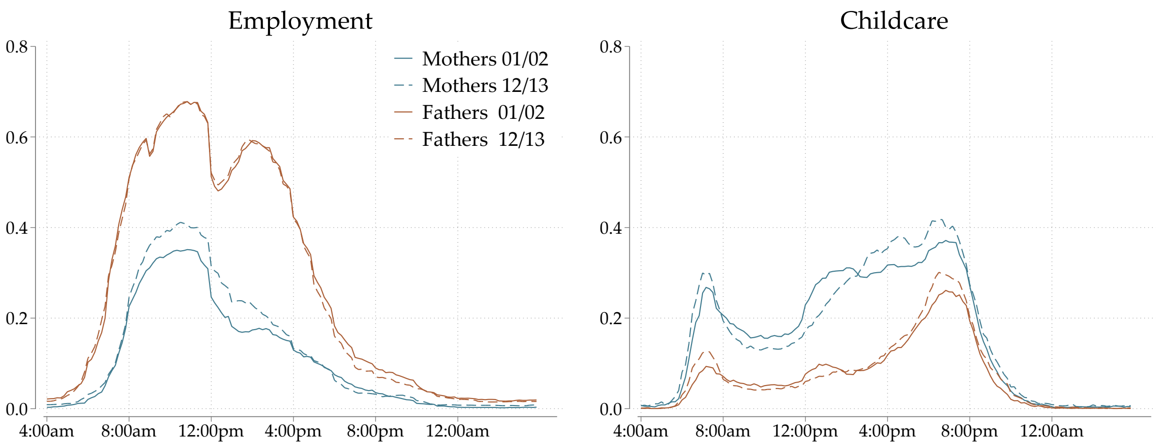
Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows the relationship between within-person changes in potential wages and within-person changes in observed wages for mothers and fathers using different lags of the labor market shocks. The sample spans the years 2005 to 2019 and includes two-parent households aged 18–63 with a resident child aged 2–10. The assumed lag structure is indicated in the figure titles. Solid lines show estimates from a linear regression of actual wages on potential wages controlling for individual fixed effects and year fixed effects. Whiskers show 95% confidence intervals; standard errors are clustered at the individual level. Binned scatters are constructed using the optimal binning procedure of Cattaneo et al. (2024).

FIGURE S.8 – Impact of a 10% increase in maternal/paternal wages on parental working hours by vingtile



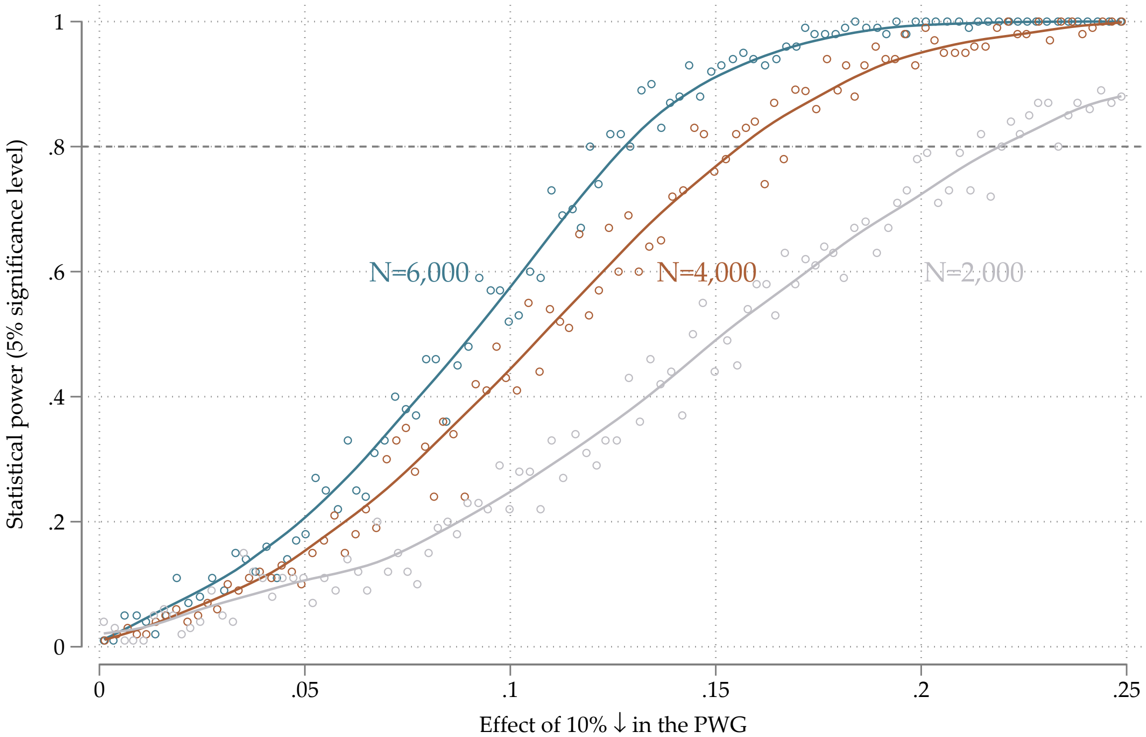
Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows estimates for the impact of a 10% increase of maternal (paternal) potential wages on maternal and paternal working hours at different vingtiles of the corresponding hours distribution. Point estimates for maternal (paternal) potential wages are derived from unconditional quantile regressions (Firpo et al., 2009). Shaded areas show the corresponding 95% confidence intervals (capped at -10/10 for better visibility). Dashed vertical lines show the extensive labor supply margin in the unconditional initial working hours distribution. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects. Standard errors are clustered at the family level.

Figure S.9 – Time-use of mothers and fathers in Germany, 2001/02 and 2012/13



Data: GTUS.
Note: Own calculations. This figure shows the share of mothers and fathers involved in employment and childcare activities for each 10-minute time window of the day. The samples include two-parent households aged 18–63 with at least one resident child below age 17. All variables refer to week days (Monday–Friday).

Figure S.10 – Ex-post power calculations



Data: Simulation.
Note: Own calculations. This figure shows power curves for three different sample sizes. Simulations are based on an error term with $\mathcal{N} = (0.00, 0.67)$ and a regressor with $\mathcal{N} = (0.00, 0.19)$. These specifications correspond to Openness and the PWG after residualizing them from family times age fixed effects and year fixed effects. For each sample size, I estimate 10,000 regressions where the coefficient is drawn from a uniform distribution across the interval [0.00, 0.25]. The graph is constructed after ordering estimations by the assumed effect size and binning 10,000 estimations into percentiles. Lowess plots are fitted using a bandwidth of 0.3.

B ADDITIONAL TABLES

TABLE S.1 – Definition of socio-emotional skills

Panel (a): Big Five Personality Traits	
Openness	... the tendency to be open to new aesthetic, cultural, or intellectual experiences.
Conscientiousness	... the tendency to be organized, responsible, and hardworking.
Extraversion	... the tendency to be outgoing, gregarious, sociable, and openly expressive.
Agreeableness	... the tendency to act in a cooperative, unselfish manner.
Neuroticism	... a chronic level of emotional instability and proneness to psychological distress.
Panel (b): Externalizing-Internalizing Behavior	
Externalizing	... reactions to stressors through actions in the external world, such as acting out, antisocial behavior, hostility, and aggression.
Internalizing	... reactions to stressors through processes within the self, such as anxiety, somatization, and depression.

Note: Short definitions from the APA Dictionary of Psychology.

TABLE S.2 – Socio-emotional skill scales in the GSOEP by age group

Age group/ (Likert scale)	Dimension	Questions
2–3 years (11-point Likert)		*How would you rank your child in comparison to other children of the same age? My child is ...*
	Openness	quick at learning new things – needs more time
	Conscientiousness	focused – easily distracted
	Extraversion	shy – outgoing
	Agreeableness	obstinate – obedient
	Neuroticism	–
5–6 years 9–10 years (11-point Likert)		*How would you rank your child in comparison to other children of the same age? My child is ...*
	Openness	not that interested – hungry for knowledge understands quickly – needs more time
	Conscientiousness	tidy – untidy focused – easy to distract
	Extraversion	talkative – quiet withdrawn – sociable
	Agreeableness	good-natured – irritable obstinate – compliant
	Neuroticism	self-confident – insecure fearful – fearless
5–6 years 9–10 years (7-point Likert)		*To what extent do the following statements apply to your child?*
	Externalizing	Often has tantrums, has a temper Quarrels a lot with other children, picks on them Is agitated, hyperactive, cannot sit still Is fidgety Is easily distracted and lacks concentration Finishes tasks, is able to concentrate Thinks before acting
	Internalizing	Is often unhappy or dejected Is nervous or clingy in new situations, loses self-confidence easily Has many fears, becomes frightened easily Is a loner, usually plays by him/herself Is popular with other children Is often made fun of or picked on by other children Gets along better with adults than with other children

TABLE S.3 – Inter-temporal persistence of children's socio-emotional skills

	Big Five Personality Traits					Strength and Difficulty Questionnaire	
	Open-ness (1)	Conscientious-ness (2)	Extra-version (3)	Agreeable-ness (4)	Neuro-ticism (5)	External-izing (6)	Internal-izing (7)
Panel (a): Ordinary least squared							
Lagged skill	0.390*** (0.024)	0.367*** (0.022)	0.428*** (0.022)	0.401*** (0.021)	0.409*** (0.021)	0.574*** (0.028)	0.495*** (0.028)
Controls	✓	✓	✓	✓	✓	✓	✓
N	2,449	2,443	2,451	2,436	2,350	1,262	1,379
R^2	0.224	0.189	0.241	0.220	0.218	0.402	0.307
Outcome Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outcome SD	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Panel (b): IV (2SLS)							
Lagged skill	0.779*** (0.076)	0.659*** (0.076)	0.705*** (0.052)	0.791*** (0.071)	–	–	–
Controls	✓	✓	✓	✓	–	–	–
N	2,449	2,443	2,451	2,436	–	–	–
R^2	0.001	0.046	0.104	0.009	–	–	–
Outcome Mean	0.000	0.000	0.000	0.000	–	–	–
Outcome SD	1.000	1.000	1.000	1.000	–	–	–

Data: GSOEP.
Note: Own calculations. This table shows inter-temporal correlations of children's socio-emotional skills. All skill measures are standardized on the estimation sample. This sample differs from the core analysis sample: I do not restrict the sample to the availability of corresponding sibling and parental investment data. Furthermore, the sample is restricted to children with 3 (Columns [1]–[4]) and 2 (Columns [5]–[7]) measures of socio-emotional skills. Panel (a) shows results from OLS regressions of children's socio-emotional skills on 1-period lags of the same skill. Panel (b) shows results from 2SLS regressions of children's socio-emotional skills on 1-period lags of the same skill. The 1-period lags are instrumented with 2-period lags of the same skill. All regressions control non-parametrically for maternal/paternal education, birth order, number of siblings, biological sex, birth month, CZ of residence, and year fixed effects. Standard errors (in parentheses) are clustered at the child level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.4 – Parental wages and family formation

	Parental separation within 5 years		Maternal fertility within 5 years	
	Sibling model (1)	Child model (2)	Sibling model (3)	Child model (4)
Effect of 10% ↑ in parental wages				
Mother	0.047 (0.038)	0.008 (0.020)	0.004 (0.050)	-0.024 (0.040)
Father	0.007 (0.010)	0.004 (0.008)	-0.058** (0.025)	-0.010 (0.024)
Panel (b): Effect of 10% ↓ in PWG				
PWG	0.020 (0.019)	0.002 (0.011)	0.031 (0.028)	-0.007 (0.025)
Family × child age FE	✓	×	✓	×
First differences	×	✓	×	✓
Year FE	✓	✓	✓	✓
N	5,484	6,986	5,484	6,302
Outcome Mean	0.036	0.032	0.129	0.112
Outcome SD	0.187	0.177	0.335	0.315

Data: GSOEP.
Note: Own calculations. This table shows changes in family outcomes in response to changes in maternal and paternal potential wages. Columns (1) and (2) consider whether the parents of the child will separate within the next 5 years. Columns (3) and (4) consider whether the mother of the child will have another child within the next 5 years. The sibling models are estimated using the specifications of equations 3 and 4, respectively. The child models are estimated in first differences across the child ages of 3, 6, and 10, and include non-parametric controls for year, child age, child sex, CZ of residence, and education level of the highest educated parents. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.5 – Summary statistics by sample restriction

	All children N=34,962		All siblings N=16,958		Core sample N=5,484	
	Mean	SD	Mean	SD	Mean	SD
Panel (a): Child characteristics						
Age	5.95	2.52	6.12	2.49	6.18	2.86
Birth rank	1.98	1.06	2.05	1.06	2.05	1.03
East Germany	0.20	0.40	0.19	0.39	0.19	0.40
Female	0.49	0.50	0.49	0.50	0.49	0.50
Migration background	0.04	0.18	0.02	0.13	0.02	0.12
Panel (b): Parental investments						
Formal care (yes/no)	0.66	0.47	0.64	0.48	0.66	0.48
Informal care (yes/no)	0.29	0.45	0.29	0.46	0.29	0.46
Parental care (hours/day)	9.49	5.01	9.87	5.06	9.89	5.20
Share maternal earnings (in %)	20.56	23.59	19.13	22.88	19.20	22.99
Total disp. family income (in Thsd. €)	43.49	25.74	46.00	27.72	46.02	25.99

Data: GSOEP.
Note: Own calculations. This table shows summary statistics for different data restrictions. All samples span the years 2005 to 2019 and include two-parent households aged 18–63 with a resident child aged 2–10. The left panel restricts the sample to families with valid measurements of the variables shown in this table. The central panel further restricts the sample to families with at least two siblings who are observed at the same chronological age. The right panel further restricts the sample to observations with at least one valid measurement of children's socio-emotional skills. This is the core analysis sample.

TABLE S.6 – Comparison GSOEP and GTUS: Work and childcare in 2001/02 and 2012/13

	GSOEP		GTUS	
	2001/02	2012/13	2001/02	2012/13
Panel (a): Mothers				
Work (hours/day)	3.2	2.9	2.7	3.4
Childcare (hours/day)	5.9	5.7	4.6	4.7
Time investment (hours/day)	–	–	1.5	1.5
Panel (b): Fathers				
Work (hours/day)	8.9	7.9	7.2	7.3
Childcare (hours/day)	1.5	1.8	2.0	2.1
Time investment (hours/day)	–	–	0.5	0.6

Data: GSOEP, GTUS.
Note: Own calculations. This table compares time-use variables in the GSOEP and the GTUS. The samples include two-parent households aged 18–63 with at least one resident child below age 17. All variables refer to week days (Monday–Friday). In the GTUS, *Childcare (hours/day)* capture any activity with the child present. *Time investment (hours/day)* capture any time when respondents consider childcare as their primary activity.

TABLE S.7 – Comparison SIAB and MZ: Employment structure by year

	1995		2005		2015	
	SIAB	MZ	SIAB	MZ	SIAB	MZ
Panel (a): Occupation (employment share, in %)						
Farming/Gardening Occ. (Low)	1.9	2.2	1.5	1.7	1.2	1.4
Construction Occ. (High)	0.9	1.6	0.7	1.3	1.2	1.5
Science/IT Occ. (Low)	1.3	1.0	1.1	0.9	1.2	1.2
Science/IT Occ. (High)	1.5	1.7	2.4	2.7	2.4	3.1
Logistics Occ. (Low)	13.8	11.7	13.7	11.0	13.4	11.3
Logistics Occ. (High)	0.1	0.9	0.2	0.9	0.7	1.1
Purchasing/Sales (Low)	9.2	8.5	9.8	10.0	10.0	10.5
Purchasing/Sales (High)	0.8	1.9	0.8	2.0	2.5	2.5
Administrative Occ. (All)	21.7	22.9	23.6	23.3	21.7	22.9
Medical Care Occ. (Low)	5.5	6.8	6.6	8.9	7.6	6.7
Medical Care Occ. (High)	1.0	1.4	1.5	1.9	2.7	2.4
Farming/Gardening Occ. (High)	0.2	0.1	0.1	0.1	0.2	0.3
Education/Social Care Occ. (All)	5.5	5.1	6.9	5.9	7.3	6.6
Creative Occ. (Low)	0.5	0.3	0.5	0.3	0.3	0.3
Creative Occ. (High)	0.4	0.6	0.5	0.7	0.6	0.8
Raw Material Processing Occ. (Low)	8.2	8.8	7.2	6.7	6.0	4.9
Raw Material Processing Occ. (High)	0.1	0.3	0.1	0.2	0.3	0.4
Machine-Building Occ. (Low)	10.0	11.1	9.1	10.3	8.5	9.5
Machine-Building Occ. (High)	4.8	3.5	5.1	4.1	4.3	5.3
Commodity Prod. Occ. (All)	3.9	3.1	3.4	2.8	2.9	2.5
Commodity Prod. Occ. (High)	0.0	0.1	0.0	0.1	0.2	0.3
Construction Occ. (Low)	8.7	6.3	5.3	4.1	4.8	4.6
Panel (b): Industry (employment share, in %)						
Agriculture/Mining/Utilities	3.2	4.3	2.8	3.2	2.3	2.9
Finance/Insurance	3.6	4.0	3.7	4.0	3.0	3.6
Public Administration	7.0	7.4	5.9	6.7	5.2	5.9
Education	3.2	3.9	3.5	4.3	3.7	4.5
Human Health Services	9.0	9.5	11.5	12.4	13.1	11.3
Other	3.7	2.5	4.0	2.8	3.7	3.9
Manufacturing: Food/Textiles	7.9	8.4	6.4	6.4	5.4	6.1
Manufacturing: Raw Materials/Metals/Chemicals	8.5	8.4	7.7	7.4	6.8	6.6
Manufacturing: Electronics/Vehicles/Machinery	9.4	8.3	9.5	9.1	8.7	11.0
Construction	10.6	11.2	6.4	7.3	5.5	6.8
Wholesale/Retail	15.2	15.6	15.0	15.4	14.0	15.4
Transportation/Storage	5.1	4.5	5.4	4.7	5.4	5.3
Accommodation/Food Services	2.8	2.3	3.1	3.0	3.5	3.3
Information/Communication/Business Services	10.9	9.7	15.3	13.3	19.7	13.3

Data: SIAB, MZ.
Note: Own calculations. This table shows the employment structure of the SIAB and the MZ in the years 1995, 2005, and 2015. All statistics are calculated on the sample of employees aged 18–63. The MZ is restricted to match the sample characteristics of the SIAB by excluding the marginally employed (<10h/week), civil servants, and self-employed individuals. Occupation classes are separated by their skill requirement (in parentheses).

TABLE S.8 – Comparison SIAB and MZ: Socio-demographics by year

	1995		2005		2015	
	SIAB	MZ	SIAB	MZ	SIAB	MZ
Panel (a): Age (average in employed population)						
Age	38.4	38.4	40.3	39.9	41.9	42.0
Panel (b): Sex (employment share, in %)						
Male	57.5	55.2	55.4	52.8	53.7	53.5
Female	42.5	44.8	44.6	47.2	46.3	46.5
Panel (c): Education (employment share, in %)						
Low	10.7	13.1	8.0	12.7	6.5	9.7
Intermediate	73.0	67.4	68.2	62.3	60.0	58.5
High	16.3	19.5	23.9	25.0	33.4	31.8
Panel (d): Federal state (employment share, in %)						
Schleswig-Holstein	2.9	3.3	2.9	3.5	3.0	3.0
Saarland	1.3	1.1	1.3	1.1	1.2	1.1
Berlin	4.7	4.3	4.0	3.8	4.4	3.8
Brandenburg	3.3	3.5	2.7	3.3	2.7	3.2
Mecklenburg-Vorpommern	2.4	2.5	2.0	2.0	1.8	1.8
Sachsen	6.2	6.2	5.2	5.8	5.1	5.1
Sachsen-Anhalt	3.7	3.7	2.9	3.3	2.6	2.9
Thüringen	3.3	3.6	2.8	3.1	2.6	2.9
Hamburg	2.7	2.0	2.9	2.1	3.0	1.8
Niedersachsen	8.2	8.4	8.5	7.8	8.7	10.2
Bremen	1.3	0.8	1.2	0.7	1.2	0.7
Nordrhein-Westfalen	20.5	19.9	21.1	19.5	20.6	19.2
Hessen	7.5	7.1	7.9	7.8	7.8	7.8
Rheinland-Pfalz	4.1	4.9	4.3	4.9	4.3	4.7
Baden-Württemberg	13.1	13.0	14.0	14.0	14.1	14.0
Bayern	15.0	15.6	16.2	17.1	16.9	17.7

Data: SIAB, MZ.
Note: Own calculations. This table shows the socio-demographic composition of the SIAB and the MZ in the years 1995, 2005, and 2015. All statistics are calculated on the sample of employees aged 18–63. The MZ is restricted to match the sample characteristics of the SIAB by excluding the marginally employed (<10h/week), civil servants, and self-employed individuals. Education is classified as follows: Lower secondary degree without tertiary education (*Low*), lower secondary degree with vocational training or higher secondary degree without vocational training (*Intermediate*), university qualification (*High*).

TABLE S.9 – Industry employment shares by gender and education, 1995

	Male			Female		
	Low	Inter–mediate	High	Low	Inter–mediate	High
Agriculture/Mining/Utilities	5.8	4.5	3.2	1.5	1.7	1.5
Manufacturing: Food/Textiles	11.4	8.5	4.6	13.3	7.4	3.3
Manufacturing: Raw Materials/Metals/Chemicals	19.2	11.5	7.7	8.7	3.7	3.3
Manufacturing: Electronics/Vehicles/Machinery	11.8	12.6	14.3	10.3	4.1	3.5
Construction	13.8	19.1	6.2	1.3	3.1	2.5
Wholesale/Retail	8.8	13.9	10.1	12.3	20.9	11.8
Transportation/Storage	6.5	7.1	3.3	2.1	3.7	2.3
Accommodation/Food Services	5.1	2.0	0.9	7.0	3.7	1.6
Information/Communication/Business Services	8.3	8.3	19.8	11.8	10.5	17.6
Finance/Insurance	0.6	2.4	6.2	2.5	4.5	6.9
Public Administration	4.3	4.7	6.2	8.3	9.9	10.3
Education	0.6	0.9	6.2	3.3	3.9	12.0
Human Health Services	1.7	2.5	7.2	12.8	17.5	17.5
Other	2.2	2.0	4.2	4.7	5.4	5.7

Data: SIAB.
Note: Own calculations. This table shows the employment share of each industry among employees aged 18–63 in 1995 by gender and education. Education is classified as follows: Lower secondary degree without tertiary education (*Low*), lower secondary degree with vocational training or higher secondary degree without vocational training (*Intermediate*), university qualification (*High*).

TABLE S.10 – Occupation employment shares by gender and education, 1995

	Male			Female		
	Low	Inter–mediate	High	Low	Inter–mediate	High
Farming/Gardening Occ. (Low)	4.5	2.2	0.7	1.6	1.7	0.4
Farming/Gardening Occ. (High)	0.1	0.1	0.5	0.1	0.1	0.2
Raw Material Processing Occ. (Low)	24.4	13.6	1.9	8.9	1.6	0.3
Raw Material Processing Occ. (High)	0.0	0.1	0.4	0.0	0.0	0.0
Machine-Building Occ. (Low)	8.8	17.7	4.0	9.4	3.4	1.6
Machine-Building Occ. (High)	0.9	5.2	20.5	0.4	0.9	3.4
Commodity Prod. Occ. (All)	6.9	3.5	0.6	13.1	4.2	0.6
Commodity Prod. Occ. (High)	0.0	0.0	0.0	0.0	0.0	0.0
Construction Occ. (Low)	16.1	17.3	2.1	0.6	0.7	0.2
Construction Occ. (High)	0.1	0.5	5.7	0.0	0.1	1.7
Science/IT Occ. (Low)	2.6	1.6	0.7	1.4	0.8	0.8
Science/IT Occ. (High)	0.3	0.9	8.4	0.2	0.4	3.0
Logistics Occ. (Low)	27.8	17.8	4.1	33.4	8.2	1.7
Logistics Occ. (High)	0.1	0.1	0.5	0.0	0.0	0.1
Purchasing/Sales (Low)	3.3	4.9	4.3	9.9	18.2	6.4
Purchasing/Sales (High)	0.1	1.2	1.8	0.0	0.2	0.6
Administrative Occ. (All)	2.7	10.4	27.3	11.4	36.8	41.2
Medical Care Occ. (Low)	0.4	1.2	1.2	3.0	13.7	7.8
Medical Care Occ. (High)	0.0	0.2	3.9	0.1	0.6	6.2
Education/Social Care Occ. (All)	0.5	0.9	9.2	6.4	7.9	21.6
Creative Occ. (Low)	0.4	0.6	0.4	0.3	0.4	0.9
Creative Occ. (High)	0.1	0.2	1.7	0.1	0.1	1.3

Data: SIAB.
Note: Own calculations. This table shows the employment share of each occupation among employees aged 18–63 in 1995 by gender and education. Education is classified as follows: Lower secondary degree without tertiary education (*Low*), lower secondary degree with vocational training or higher secondary degree without vocational training (*Intermediate*), university qualification (*High*). Occupation classes are separated by their skill requirement (in parentheses).

Table S.11 – Predictive power of pre-determined characteristics for children's socio-emotional skills

	Big Five Personality Traits					SDQ	
	Openness (1)	Conscientiousness (2)	Extraversion (3)	Agreeableness (4)	Neuroticism (5)	Externalizing (6)	Internalizing (7)
Female	-0.072* (0.038)	-0.001 (0.039)	0.049 (0.039)	-0.057 (0.038)	0.029 (0.054)	0.068 (0.055)	-0.042 (0.055)
Born before October	-0.011 (0.046)	-0.006 (0.047)	0.023 (0.045)	-0.057 (0.047)	0.040 (0.061)	0.045 (0.067)	-0.085 (0.068)
Birth year	-0.013* (0.007)	-0.010 (0.007)	0.007 (0.007)	-0.004 (0.007)	0.015 (0.011)	0.031*** (0.011)	0.022** (0.011)
Firstborn	0.160*** (0.047)	-0.041 (0.048)	-0.188*** (0.049)	0.127*** (0.048)	0.266*** (0.068)	-0.007 (0.071)	0.208*** (0.072)
# of siblings	-0.031 (0.022)	-0.011 (0.022)	-0.027 (0.022)	0.041* (0.023)	0.025 (0.031)	-0.010 (0.034)	0.024 (0.033)
Birth height (cm)	-0.017* (0.010)	0.016 (0.010)	-0.016* (0.009)	-0.003 (0.009)	-0.007 (0.013)	-0.002 (0.013)	-0.004 (0.014)
Birth weight (kg)	0.173*** (0.051)	-0.011 (0.052)	0.063 (0.048)	0.045 (0.051)	0.004 (0.071)	-0.095 (0.072)	0.002 (0.076)
Days in hospital (3 months post-birth)	-0.002 (0.003)	0.001 (0.002)	-0.004* (0.002)	0.004* (0.002)	0.008** (0.004)	-0.005 (0.004)	0.003 (0.005)
Age at birth (Mother)	0.022*** (0.006)	0.009 (0.006)	0.001 (0.006)	0.010* (0.005)	-0.008 (0.007)	-0.042*** (0.008)	-0.026*** (0.008)
Age at birth (Father)	-0.009* (0.005)	0.004 (0.005)	-0.008 (0.005)	-0.001 (0.005)	0.002 (0.007)	0.007 (0.007)	0.016** (0.007)
N	2,761	2,761	2,760	2,754	1,457	1,343	1,333
R^2	0.021	0.007	0.011	0.008	0.021	0.043	0.020
Outcome Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outcome SD	1.000	1.000	1.000	1.000	1.000	1.000	1.000
Joint significance (p-value)	0.000	0.061	0.002	0.017	0.001	0.000	0.006

Data: GSOEP.
Note: Own calculations. This table shows the association of children's socio-emotional skills with pre-determined family and child characteristics. All coefficients are estimated on the sample of sibling pairs described in Table 2. The last row shows the p-value for an F-test of joint significance. Standard errors (in parentheses) are heteroskedasticity-robust. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.12 – Top 10 Rotemberg weights for mothers and fathers

Occupation/Industry	Rotemberg weights α_s	Rotemberg weights Share, in %	Coefficient β_s	Coefficient 95% CI
Panel (a): Mothers				
Purchasing/Sales (Low) in Wholesale/Retail	0.11	10.58%	6.90	[3.00,11.00]
Logistics Occ. (Low) in Information/Communication/Business Services	0.08	7.69%	2.91	[-2.50,5.50]
Education/Social Care Occ. (All) in Education	0.07	7.11%	6.52	[2.50,11.00]
Administrative Occ. (All) in Finance/Insurance	0.05	4.88%	5.70	[-6.00,15.00]
Logistics Occ. (Low) in Human Health Services	0.04	4.17%	5.10	[0.50,8.00]
Commodity Prod. Occ. (All) in Manufacturing: Food/Textiles	0.03	3.12%	8.21	[5.00,14.50]
Medical Care Occ. (High) in Human Health Services	0.03	3.02%	0.30	[-16.00,9.50]
Medical Care Occ. (Low) in Human Health Services	0.03	2.87%	8.82	[-1.00,30.00]
Purchasing/Sales (Low) in Manufacturing: Food/Textiles	0.03	2.63%	7.83	[3.00,13.00]
Logistics Occ. (Low) in Wholesale/Retail	0.03	2.54%	6.63	[3.50,9.50]
Panel (b): Fathers				
Machine-Building Occ. (High) in Manufacturing: Electronics/Vehicles/Machinery	0.18	17.11%	0.80	[-1.00,2.50]
Construction Occ. (Low) in Construction	0.11	10.93%	2.31	[1.00,4.00]
Science/IT Occ. (High) in Information/Communication/Business Services	0.04	4.34%	1.37	[0.00,3.00]
Administrative Occ. (All) in Manufacturing: Electronics/Vehicles/Machinery	0.04	4.22%	1.02	[-1.00,3.00]
Logistics Occ. (Low) in Transportation/Storage	0.04	4.17%	1.99	[0.00,4.50]
Machine-Building Occ. (High) in Information/Communication/Business Services	0.03	3.22%	2.38	[1.00,4.00]
Logistics Occ. (Low) in Information/Communication/Business Services	0.03	2.56%	2.08	[-1.50,6.50]
Raw Material Processing Occ. (Low) in Manufacturing: Raw Materials/Metals/Chemicals	0.03	2.54%	3.38	[1.00,6.50]
Administrative Occ. (All) in Finance/Insurance	0.03	2.50%	2.99	[-1.00,12.00]
Medical Care Occ. (High) in Human Health Services	0.03	2.50%	0.08	[-4.00,3.50]

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows the 10 economic sectors with the highest Rotemberg weights for mothers and fathers. Rotemberg weights (α_s) are calculated on the core sample described in Table 1 using the programming routine provided by Goldsmith-Pinkham et al. (2020). The share of each Rotemberg weight is calculated by dividing α_s with $\sum_s[\alpha_s|\alpha_s \geq 0]$. β_s is the coefficient of $\hat{w}^m_{it-1}$ ($\hat{w}^p_{it-1}$) from a just-identified 2SLS regression of maternal (paternal) labor income on $\hat{w}^m_{it-1}$ ($\hat{w}^p_{it-1}$) where $\hat{w}^m_{it-1}$ ($\hat{w}^p_{it-1}$) is instrumented with the group-specific sector share in base year 1995 ($E^s_{g,1995}/E_{g,1995}$) while controlling for family times child age fixed effects and year fixed effects. The confidence interval is the weak instrument robust confidence interval of Chernozhukov and Hansen (2008) over the interval $[-30, 30]$.

TABLE S.13 – Parental wages and parental labor force participation

	Mother			Father		
	Hours per day (1)	Employed (yes/no) (2)	Hours per day if working (3)	Hours per day (4)	Employed (yes/no) (5)	Hours per day if working (6)
Panel (a): Effect of 10% ↑ in parental wages						
Mother	1.230*** (0.375)	0.139*** (0.045)	-0.185 (0.565)	-0.181 (0.572)	-0.044 (0.058)	0.193 (0.288)
Father	-0.482*** (0.156)	-0.066** (0.027)	0.002 (0.169)	0.498** (0.224)	0.020 (0.021)	0.428*** (0.158)
Family × child age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
N	5,484	5,484	2,658	5,484	5,484	4,850
R^2	0.798	0.758	0.837	0.778	0.745	0.798
Outcome Mean	3.413	0.590	5.927	8.743	0.915	9.591
Outcome SD	3.456	0.492	2.501	3.208	0.279	1.811

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental labor force participation in response to changes in maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.14 – Robustness: 10% decrease in the PWG and socio-emotional skills

	Big Five Personality Traits					SDQ	
	Openness (1)	Conscientiousness (2)	Extraversion (3)	Agreeableness (4)	Neuroticism (5)	Externalizing (6)	Internalizing (7)
Baseline	-0.032 (0.069)	-0.011 (0.070)	0.108* (0.064)	-0.040 (0.066)	0.015 (0.112)	0.181 (0.136)	-0.024 (0.091)
Panel (a): Alternative construction of potential wages							
No imputation	-0.045 (0.081) [5,443]	-0.004 (0.082) [5,453]	0.127 (0.078) [5,443]	-0.058 (0.078) [5,432]	0.030 (0.137) [3,597]	0.221 (0.167) [2,273]	-0.029 (0.113) [2,262]
CPS imputation	-0.035 (0.069) [5,443]	-0.013 (0.071) [5,453]	0.103 (0.064) [5,443]	-0.048 (0.066) [5,432]	0.018 (0.114) [3,597]	0.184 (0.139) [2,273]	-0.024 (0.092) [2,262]
Updating (Shenhav, 2021)	-0.022 (0.071) [5,443]	-0.014 (0.073) [5,453]	0.106 (0.065) [5,443]	-0.049 (0.067) [5,432]	0.025 (0.114) [3,597]	0.189 (0.139) [2,273]	-0.019 (0.092) [2,262]
Updating ($t-10$)	-0.008 (0.064) [5,443]	0.012 (0.064) [5,453]	0.100 (0.062) [5,443]	-0.038 (0.062) [5,432]	-0.068 (0.114) [3,597]	0.090 (0.119) [2,273]	-0.015 (0.090) [2,262]
Daily wages	-0.002 (0.066) [5,443]	-0.034 (0.069) [5,453]	0.072 (0.062) [5,443]	-0.033 (0.061) [5,432]	0.011 (0.109) [3,597]	0.166 (0.123) [2,273]	-0.043 (0.090) [2,262]
Panel (b): Alternative control variables							
Child characteristics	-0.041 (0.069) [5,443]	-0.021 (0.071) [5,453]	0.113* (0.063) [5,443]	-0.035 (0.067) [5,432]	0.029 (0.108) [3,597]	0.170 (0.126) [2,273]	-0.021 (0.101) [2,262]
Formal childcare availability & quality	-0.043 (0.069) [5,268]	-0.027 (0.072) [5,278]	0.122* (0.065) [5,268]	-0.043 (0.067) [5,257]	0.012 (0.111) [3,597]	0.208 (0.135) [2,273]	-0.009 (0.094) [2,262]
CZ trends	-0.073 (0.074) [5,443]	-0.070 (0.083) [5,453]	0.077 (0.069) [5,443]	-0.109 (0.076) [5,432]	0.015 (0.122) [3,597]	0.238* (0.133) [2,272]	-0.119 (0.090) [2,261]
Education trends	0.002 (0.073) [5,443]	-0.044 (0.079) [5,453]	0.094 (0.068) [5,443]	-0.058 (0.071) [5,432]	-0.057 (0.116) [3,597]	0.174 (0.137) [2,273]	-0.028 (0.078) [2,262]
Panel (c): Alternative sample restrictions							
Married parents	-0.001 (0.070) [4,950]	-0.000 (0.073) [4,961]	0.126* (0.069) [4,953]	-0.018 (0.069) [4,943]	0.000 (0.116) [3,335]	0.169 (0.137) [2,107]	-0.024 (0.092) [2,097]
Biological parents	-0.036 (0.069) [5,418]	-0.014 (0.070) [5,428]	0.111* (0.064) [5,418]	-0.043 (0.066) [5,407]	0.016 (0.112) [3,576]	0.182 (0.136) [2,258]	-0.022 (0.090) [2,247]
Within-child estim.	-0.021 (0.049) [6,726]	-0.056 (0.054) [6,725]	0.039 (0.043) [6,718]	-0.020 (0.051) [6,700]	-0.013 (0.063) [3,148]	0.086 (0.088) [1,970]	-0.151* (0.087) [1,968]

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows robustness checks for changes in children's socio-emotional skills in response to a 10% decrease in the PWG (see equation 4). All robustness checks are described in section 4.3 of the paper. Sample sizes are reported in brackets. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.15 – Predictive power of socio-emotional skills for other child outcomes

	BMI at age 6: Underweight (yes/no) (1)	BMI at age 6: Overweight (yes/no) (2)	Delayed school entry (yes/no) (3)	Upper secondary school track (yes/no) (4)
Panel (a): Effect of 1 SD ↑ in children's socio-emotional skills at age 3				
Openness	-0.013 (0.008) [3,279]	-0.001 (0.006) [3,279]	-0.019*** (0.007) [2,461]	0.048*** (0.014) [1,136]
Conscientiousness	0.005 (0.008) [3,274]	-0.011* (0.006) [3,274]	-0.010 (0.006) [2,457]	0.046*** (0.015) [1,135]
Extraversion	-0.010 (0.008) [3,277]	0.004 (0.006) [3,277]	-0.007 (0.006) [2,460]	-0.002 (0.014) [1,136]
Agreeableness	0.010 (0.008) [3,270]	0.000 (0.006) [3,270]	-0.013** (0.006) [2,454]	0.015 (0.014) [1,133]
Neuroticism	–	–	–	–
Externalizing behavior	–	–	–	–
Internalizing behavior	–	–	–	–
Panel (b): Effect of 1 SD ↑ in children's socio-emotional skills at age 6				
Openness	0.003 (0.006) [5,120]	-0.018*** (0.005) [5,120]	-0.018*** (0.005) [5,120]	0.096*** (0.010) [1,887]
Conscientiousness	0.009 (0.006) [5,124]	-0.010** (0.005) [5,124]	-0.026*** (0.005) [3,671]	0.072*** (0.011) [1,891]
Extraversion	-0.009 (0.006) [5,113]	0.002 (0.004) [5,113]	-0.013*** (0.005) [3,664]	0.025** (0.011) [1,887]
Agreeableness	0.004 (0.006) [5,106]	-0.006 (0.005) [5,106]	-0.010** (0.005) [3,659]	0.052*** (0.011) [1,886]
Neuroticism	0.013** (0.006) [5,120]	-0.001 (0.004) [5,120]	0.026*** (0.005) [3,669]	-0.042*** (0.011) [1,892]
Externalizing behavior	-0.004 (0.008) [3,699]	0.019*** (0.006) [3,699]	0.033*** (0.007) [2,450]	-0.091*** (0.016) [916]
Internalizing behavior	0.001 (0.007) [3,700]	0.004 (0.006) [3,700]	0.031*** (0.006) [2,449]	-0.040** (0.016) [917]

Data: GSOEP.
Note: Own calculations. This table shows cross-sectional associations between children's socio-emotional skills at ages 3 and 6 and other child outcomes. All skill measures are standardized on the estimation sample. In Panel (a), results for neuroticism, externalizing/internalizing behavior are omitted because these skills are first measured in the mother-and-child questionnaire at age 5-6. This sample differs from the core analysis sample: I do not restrict the sample to the availability of corresponding sibling and parental investment data. All regressions control non-parametrically for maternal/paternal education, birth order, number of siblings, child sex, birth month, CZ of residence, and year fixed effects. Sample sizes are reported in brackets. Standard errors (in parentheses) are heteroskedasticity-robust. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.16 – Tests for appropriate level of clustering

		Clustering by ...			
	No clustering	Educ. (M.) × Educ. (F.) × CZ	Educ. (M.)	Educ. (F.)	CZ
	(1)	(2)	(3)	(4)	(5)
Panel (a): Big Five Personality Traits					
Openness	2.490	1.116	-0.017	-0.833	1.372
	[0.006]	[0.132]	[0.507]	[0.797]	[0.085]
Conscientiousness	2.379	-1.256	-1.044	-0.854	-1.166
	[0.009]	[0.895]	[0.852]	[0.804]	[0.878]
Extraversion	2.099	0.293	-0.942	-1.062	1.932
	[0.018]	[0.385]	[0.827]	[0.856]	[0.027]
Agreeableness	3.200	-1.072	0.225	-0.650	-0.251
	[0.001]	[0.858]	[0.411]	[0.742]	[0.599]
Emotional stability	3.048	0.844	0.359	-0.378	2.213
	[0.001]	[0.199]	[0.360]	[0.647]	[0.013]
Panel (b): Strength and Difficulty Questionnaire					
Externalizing behavior	2.822	0.376	-1.169	-0.089	1.570
	[0.002]	[0.354]	[0.879]	[0.536]	[0.058]
Internalizing behavior	2.735	1.042	1.467	-0.392	1.618
	[0.003]	[0.149]	[0.071]	[0.653]	[0.053]
Panel (c): Parental Investments					
Parental care	1.525	-1.641	-1.110	-0.892	-0.974
	[0.064]	[0.950]	[0.866]	[0.814]	[0.835]
Formal care (yes/no)	3.025	-0.067	-0.229	-1.100	0.029
	[0.001]	[0.527]	[0.591]	[0.864]	[0.488]
Informal care (yes/no)	4.680	-0.230	-1.057	-0.360	0.311
	[0.000]	[0.591]	[0.855]	[0.640]	[0.378]
Total disp. family income (in Thsd. €)	2.137	-0.246	-0.862	0.428	0.378
	[0.016]	[0.597]	[0.806]	[0.334]	[0.353]
Share maternal earnings (in %)	2.807	-1.294	0.643	-0.425	-0.572
	[0.003]	[0.902]	[0.260]	[0.665]	[0.716]

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows tests for the appropriate level of clustering following the procedures proposed in MacKinnon et al. (2023). I present the τ_σ-statistic and asymptotic p-values in brackets (see equation 20 in MacKinnon et al., 2023). τ_σ tests for the equality of the error variance matrix under the benchmark level of clustering (family-level) against the alternative indicated in the table header. Cluster tests are performed after regressing the outcomes indicated in the first column on the PWG (see equation 4). All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages.

TABLE S.17 – Parental wages and informal care provider

	Informal care			
	Any (yes/no) (1)	Family (yes/no) (2)	Friends (yes/no) (3)	Babysitter (yes/no) (4)
Panel (a): Effect of 10% ↑ in parental wages				
Mother	0.089* (0.049)	0.082* (0.045)	0.055 (0.038)	0.044 (0.032)
Father	-0.085** (0.033)	-0.050** (0.024)	-0.022 (0.013)	-0.042 (0.031)
Panel (b): Effect of 10% ↓ in PWG				
PWG	0.087*** (0.030)	0.066*** (0.025)	0.039** (0.019)	0.043* (0.023)
Family × child age FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	5,484	5,484	5,484	5,484
R^2	0.723	0.735	0.554	0.650
Outcome Mean	0.294	0.254	0.040	0.048
Outcome SD	0.456	0.435	0.196	0.213

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in the use of informal care providers in response to changes in maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects. Regressions in Panel (b) also control for the sum of maternal and paternal potential wages. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.18 – Parental wages and childcare use

	Formal care			Informal care		
	Hours per day (1)	Use (yes/no) (2)	Hours per day if using (3)	Hours per day (4)	Use (yes/no) (5)	Hours per day if using (6)
Panel (a): Effect of 10% ↑ in parental wages						
Mother	-0.023	0.055	-0.127	0.160	0.080	0.180
	(0.233)	(0.079)	(0.269)	(0.100)	(0.069)	(0.231)
Father	-0.088	-0.024	-0.012	-0.039	-0.071**	0.061
	(0.121)	(0.025)	(0.109)	(0.066)	(0.032)	(0.094)
Panel (b): Effect of 10% ↓ in PWG						
PWG	0.033	0.040	-0.058	0.099*	0.076*	0.059
	(0.132)	(0.042)	(0.150)	(0.060)	(0.039)	(0.123)
Family × child age FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
N	5,341	5,341	2,252	5,341	5,341	2,469
R^2	0.762	0.732	0.782	0.687	0.687	0.673
Outcome Mean	1.955	0.534	3.758	0.611	0.584	1.108
Outcome SD	2.202	0.499	1.653	0.972	0.493	1.113

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in childcare use in response to changes in maternal and paternal potential wages. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects. Regressions in Panel (b) also control for the sum of maternal and paternal potential wages. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.19 – Parental investments and children's socio-emotional skills

	Big Five Personality Traits					Strength and Difficulty Questionnaire	
	Open-ness (1)	Conscientious-ness (2)	Extra-version (3)	Agreeable-ness (4)	Neuro-ticism (5)	External-izing (6)	Internal-izing (7)
Parental care	0.005***	0.004*	0.006***	-0.003	-0.006**	0.001	-0.001
(hours/day)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Formal care	-0.002	-0.003	0.012***	-0.006	0.005	0.001	0.001
(hours/day)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)
Informal care	0.008	-0.003	0.008	0.003	0.011	0.031**	0.030**
(hours/day)	(0.009)	(0.009)	(0.008)	(0.008)	(0.012)	(0.014)	(0.014)
Total disp. family	0.002***	0.001*	0.002***	0.000	-0.001	-0.002***	-0.002***
income (in Thsd. €)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Share maternal earnings	0.001	-0.001	0.001**	-0.001	-0.000	0.001	0.000
(in %)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
Controls	✓	✓	✓	✓	✓	✓	✓
N	14,524	14,515	14,520	14,487	8,207	5,786	5,785
R^2	0.042	0.036	0.025	0.029	0.033	0.071	0.048
Outcome Mean	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Outcome SD	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Data: GSOEP.
Note: Own calculations. This table shows correlations between children's socio-emotional skills and parental investments. All skill measures are standardized on the estimation sample. This sample differs from the core analysis sample: I do not restrict the sample to the availability of corresponding sibling and parental investment data. All regressions control non-parametrically for maternal/paternal education, birth order, number of siblings, biological sex, birth month, CZ of residence, and year fixed effects. Standard errors (in parentheses) are clustered at the child level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S.20 – Robustness: 10% decrease in the PWG and parental investments

	Time investments			Monetary investments	
	Parental care (hours/day) (1)	Formal care (yes/no) (2)	Informal care (yes/no) (3)	Total disp. family income (in Thsd. €) (4)	Share maternal earnings (in %) (5)
Baseline	-0.232 (0.298)	0.018 (0.024)	0.087*** (0.030)	2.185** (0.882)	6.584*** (2.287)
Panel (a): Alternative construction of potential wages					
No imputation	-0.224 (0.356) [5,484]	0.027 (0.028) [5,484]	0.111*** (0.036) [5,484]	2.666** (1.048) [5,484]	7.886*** (2.695) [5,484]
CPS imputation	-0.236 (0.296) [5,484]	0.014 (0.025) [5,484]	0.090*** (0.030) [5,484]	2.101** (0.879) [5,484]	6.553*** (2.330) [5,484]
Updating (Shenhav, 2021)	-0.207 (0.291) [5,484]	0.016 (0.024) [5,484]	0.091*** (0.031) [5,484]	2.207** (0.906) [5,484]	6.585*** (2.385) [5,484]
Updating ($t-10$)	-0.197 (0.287) [5,484]	0.017 (0.026) [5,484]	0.081*** (0.029) [5,484]	1.766** (0.771) [5,484]	5.057** (2.041) [5,484]
Daily wages	-0.334 (0.293) [5,484]	0.006 (0.022) [5,484]	0.077*** (0.029) [5,484]	1.848** (0.819) [5,484]	6.046*** (2.087) [5,484]
Panel (b): Alternative control variables					
Child characteristics	-0.087 (0.295) [5,484]	0.017 (0.023) [5,484]	0.081*** (0.030) [5,484]	2.219** (0.916) [5,484]	6.391*** (2.262) [5,484]
Formal childcare availability & quality	-0.230 (0.304) [5,309]	0.020 (0.024) [5,309]	0.087*** (0.030) [5,309]	2.157** (0.887) [5,309]	6.616*** (2.319) [5,309]
CZ trends	-0.444 (0.339) [5,484]	0.008 (0.015) [5,484]	0.084** (0.036) [5,484]	2.705** (1.053) [5,484]	6.224*** (2.197) [5,484]
Education trends	-0.277 (0.335) [5,484]	0.019 (0.027) [5,484]	0.093*** (0.033) [5,484]	2.125** (0.883) [5,484]	5.144** (2.028) [5,484]
Panel (c): Alternative sample restrictions					
Married parents	-0.091 (0.303) [4,992]	0.023 (0.027) [4,992]	0.100*** (0.033) [4,992]	2.194** (0.986) [4,992]	6.140** (2.426) [4,992]
Biological parents	-0.199 (0.295) [5,459]	0.019 (0.024) [5,459]	0.087*** (0.030) [5,459]	2.166** (0.881) [5,459]	6.581*** (2.288) [5,459]
Within-child estim.	0.193 (0.244) [6,986]	0.014 (0.022) [6,986]	0.019 (0.026) [6,986]	2.218*** (0.633) [6,986]	5.583*** (1.691) [6,986]

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows robustness checks for changes in parental investments in response to a 10% decrease in the PWG (see equation 4). All robustness checks are described in section 4.3 of the paper. Sample sizes are reported in brackets. Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.21 – Decomposition of Personality Factor and Total Difficulty Score

	Personality Factor (1)	Total Difficulty Score (2)
Openness	0.488*** (0.002)	–
Conscientiousness	0.348*** (0.002)	–
Extraversion	0.317*** (0.002)	–
Agreeableness	0.321*** (0.002)	–
Neuroticism	-0.019*** (0.002)	–
Externalizing behavior	–	0.683*** (0.002)
Internalizing behavior	–	0.485*** (0.002)
N	3,589	2,724
R^2	0.988	0.993
Outcome Mean	0.000	0.000
Outcome SD	1.000	1.000

Data: GSOEP.
Note: Own calculations. This table shows the correlations of the aggregate personality factor and the aggregate total difficulty score with the underlying dimensions of socio-emotional skills. All skill measures are standardized on the estimation sample. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.22 – Heterogeneity in parental investments by child sex

Panel (a): Time investments

	Parental care		Formal care (yes/no)		Informal care (yes/no)	
	Male	Female	Male	Female	Male	Female
Effect of 10% ↓ in PWG	-0.162	-0.296	0.024	0.012	0.090***	0.084***
	(0.308)	(0.292)	(0.024)	(0.023)	(0.030)	(0.030)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	Male	Female	Male	Female
Effect of 10% ↓ in PWG	2.145**	2.237**	6.581***	6.609***
	(0.893)	(0.911)	(2.286)	(2.279)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 10% decrease in the PWG for children of different sex. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.23 – Heterogeneity in parental investments by birth order

Panel (a): Time investments

	Parental care		Formal care (yes/no)		Informal care (yes/no)	
	First	Higher	First	Higher	First	Higher
Effect of 10% ↓ in PWG	-0.244	-0.208	0.018	0.005	0.087***	0.090***
	(0.295)	(0.303)	(0.024)	(0.025)	(0.030)	(0.030)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	First	Higher	First	Higher
Effect of 10% ↓ in PWG	2.104**	2.023**	6.627***	6.524***
	(0.836)	(0.853)	(2.226)	(2.277)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 10% decrease in the PWG for children of different birth order. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.24 – Heterogeneity in parental investments by child age

Panel (a): Time investments

	Parental care		Formal care (yes/no)		Informal care (yes/no)	
	≤ 6	> 6	≤ 6	> 6	≤ 6	> 6
Effect of 10% ↓ in PWG	-0.338	0.154	0.003	0.066	0.066**	0.163***
	(0.320)	(0.563)	(0.021)	(0.056)	(0.032)	(0.043)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	≤ 6	> 6	≤ 6	> 6
Effect of 10% ↓ in PWG	2.727***	0.436	5.101**	11.558***
	(0.922)	(1.174)	(2.118)	(3.522)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 10% decrease in the PWG for children of different ages. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.25 – Heterogeneity in parental investments by region of residence

Panel (a): Time investments

	Parental care		Formal care (yes/no)		Informal care (yes/no)	
	West	East	West	East	West	East
Effect of 10% ↓ in PWG	-0.500	0.050	0.021	0.008	0.118***	0.038
	(0.389)	(0.328)	(0.026)	(0.030)	(0.038)	(0.035)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	West	East	West	East
Effect of 10% ↓ in PWG	2.896**	1.597*	5.986***	6.832**
	(1.145)	(0.909)	(2.284)	(3.150)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 10% decrease in the PWG for children in East and West Germany. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S.26 – Heterogeneity in parental investments by maternal education

Panel (a): Time investments

	Parental care		Formal care (yes/no)		Informal care (yes/no)	
	Low	High	Low	High	Low	High
Effect of 10% ↓ in PWG	-0.588	-0.218	0.009	0.010	0.113**	0.120***
	(0.542)	(0.409)	(0.058)	(0.029)	(0.045)	(0.037)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	Low	High	Low	High
Effect of 10% ↓ in PWG	0.679	3.402***	2.780	9.233***
	(1.010)	(1.084)	(2.838)	(2.452)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 10% decrease in the PWG for children of high and low educated mothers. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table S.27 – Heterogeneity in parental investments by at risk of poverty status

Panel (a): Time investments

	Parental care		Formal care (yes/no)		Informal care (yes/no)	
	$\leq$ P25	> P25	$\leq$ P25	> P25	$\leq$ P25	> P25
Effect of 10% ↓ in PWG	-0.388	-0.400	0.015	0.031	0.088***	0.075**
	(0.290)	(0.482)	(0.021)	(0.031)	(0.030)	(0.034)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	$\leq$ P25	> P25	$\leq$ P25	> P25
Effect of 10% ↓ in PWG	1.955**	2.606**	6.945***	5.899**
	(0.859)	(1.220)	(2.239)	(2.374)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 10% decrease in the PWG for children by poverty status of the family. All coefficients are estimated on the core sample described in Table 1. All regressions control for family times child age fixed effects and year fixed effects, and the sum of maternal and paternal potential wages (interacted with the corresponding heterogeneity variable). Standard errors (in parentheses) are clustered at the family level. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

C MEASUREMENT ERROR CORRECTION

Basic set-up. Assume that outcome y^* is measured with error and that measurement error is classical:

$$y_{it} = y^*_{it} + \eta_{it},$$

where $y \sim \mathcal{N}(0,1)$, $\eta \sim \mathcal{N}(0,\sigma^2_\eta)$, $Cov(X,\eta) = 0$, and $Cov(y^*,\eta) = 0$.

In this case, equation 4 can be re-written as follows:

$$y_{it} = \alpha + \beta^\Delta \underbrace{(\ln \hat{w}^m_{it-1} - \ln \hat{w}^p_{it-1})}_{=\hat{w}^\Delta_{it-1}} + \beta^\Sigma \underbrace{(\ln \hat{w}^m_{it-1} + \ln \hat{w}^p_{it-1})}_{=\hat{w}^\Sigma_{it-1}} + \gamma_{f(i)a(it)} + \tau_t + X'_{it}\delta + \epsilon^*_{it} + \eta_{it},$$

where ϵ^* is the true error term.

Estimation of measurement error. Suppose we have two noisy measures of y^* such that $y^1, y^2 \sim \mathcal{N}(0,1)$. Then, we can estimate $\sigma^2_{y^*}$ by regressing y^1 on y^2 (e.g., Gillen et al., 2019):

$$\hat{\delta} = \frac{Cov(y^*_{it} + \eta^1_{it}, y^*_{it} + \eta^2_{it})}{Var(y^2_{it} + \eta^2_{it})} = \frac{Cov(y^*_{it}, y^*_{it})}{Var(y^2_{it} + \eta^2_{it})} = \frac{Var(y^*_{it})}{Var(y^2_{it} + \eta^2_{it})} = \sigma^2_{y^*}.$$

Under our maintained assumptions it must be the case that $\sigma^2_y = \sigma^2_{y^*} + \sigma^2_\eta$, and we get:

$$\sigma^2_\eta = \sigma^2_y - \sigma^2_{y^*} = 1 - \hat{\delta}.$$

I can implement this estimation strategy in my data for a subsample of children at age 10. In waves 2010–2013, GSOEP collected data on children's Big 5 personality traits from both parents of children in this age group. Thus, for these children we have two noisy measures of the same outcome allowing us to estimate σ^2_η in this subsample.

Table S.28 shows the results of this estimation. The estimated value of δ $(= 1 - \sigma^2_\eta)$ is above 0.5 for all Big 5 personality traits except for Neuroticism. Furthermore, we can use these estimates to correct standard errors for measurement error in the dependent variable.

Table S.28 – Estimation of measurement error

	Big Five Personality Traits at age 10				
	Open-ness (1)	Conscientious-ness (2)	Extra-version (3)	Agreeable-ness (4)	Neuro-ticism (5)
δ	0.620*** (0.026)	0.639*** (0.024)	0.581*** (0.028)	0.519*** (0.029)	0.493*** (0.027)
Controls	×	×	×	×	×
N	1,083	1,083	1,083	1,083	1,083
R^2	0.385	0.408	0.337	0.270	0.243
Outcome Mean	0.000	0.000	0.000	0.000	0.000
Outcome SD	1.000	1.000	1.000	1.000	1.000

Data: GSOEP.
Note: Own calculations. This table shows correlations of maternal and paternal reports on children's socio-emotional skills. All skill measures are standardized on the estimation sample. This sample differs from the core analysis sample: I do not restrict the sample to the availability of corresponding sibling and parental investment data. Furthermore, the sample is restricted to children with maternal and paternal reports of socio-emotional skills. Standard errors (in parentheses) are heteroskedasticity-robust. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Measurement error correction. I cluster standard errors at level g, i.e., the family-level in our baseline estimates. Therefore, the formula for the variance-covariance matrix reads as follows:

$$\hat{V}(\hat{\beta}) = \left(X'X\right)^{-1} \left(\sum_{g=1}^{G} X_g' \hat{\epsilon}_g \hat{\epsilon}_g' X_g \right) \left(X'X\right)^{-1},$$

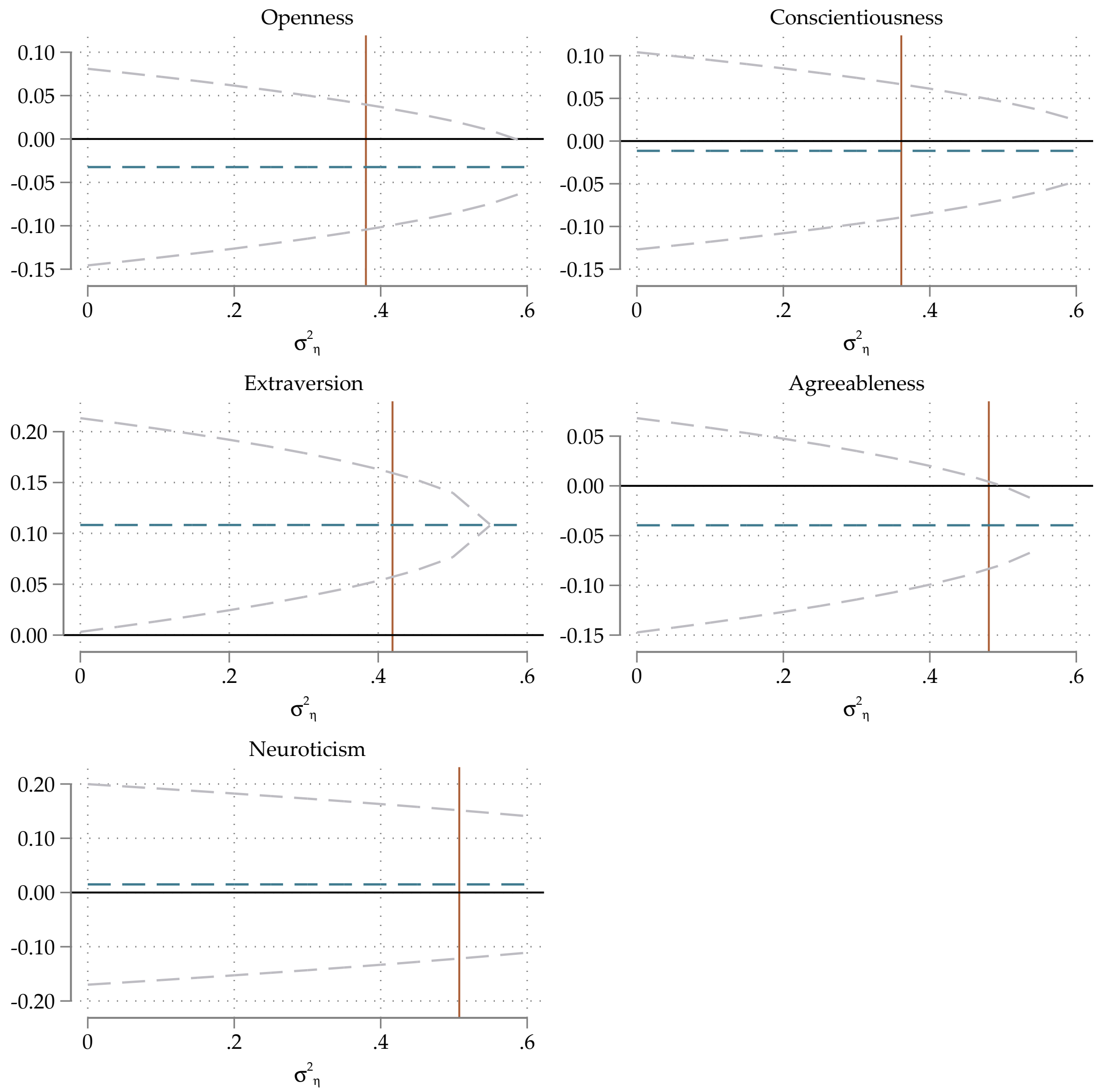
where, with a slight divergence from equation 4, we use X to represent the matrix of all independent variables.

Assuming that $\eta_g \eta_g'$ is invariant across clusters g, we can adjust $\hat{V}(\hat{\beta})$ for measurement error as follows:

$$\begin{aligned} \hat{V}^*(\hat{\beta}) &= \left(X'X\right)^{-1} \left(\sum_{g=1}^{G} X_g' \left(\hat{\epsilon}_g \hat{\epsilon}_g' - \sigma_\eta^2 I_g \right) X_g \right) \left(X'X\right)^{-1}, \\ &= \hat{V}(\hat{\beta}) - \sigma_\eta^2 \left(X'X\right)^{-1} \left(\sum_{g=1}^{G} X_g' X_g \right) \left(X'X\right)^{-1}. \end{aligned} \tag{6}$$

Figure S.11 shows the impact of this standard error correction for estimates of β^Δ in equation 4 under different assumptions about σ_η^2. A value of $\sigma_\eta^2 = 0$ corresponds to the baseline estimates shown in Table 4. The vertical lines show estimates based on δ (see Table S.28). As expected, the

FIGURE S.11 – Robustness of standard errors to measurement error correction



Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows treatment effects (dashed horizontal lines) and 95% confidence bands (dashed gray lines) for a 10% decrease in the PWG under different assumptions about measurement error in the outcome variables. Standard errors are corrected using the formula shown in equation 6, where σ^2_η is taken over the interval [0.00(0.05)0.60]. $\sigma^2_\eta = 0$ replicates the baseline result shown in Table 4. Vertical lines show estimates of σ^2_η using concurrent reports of mothers and fathers on children's socio-emotional skills at age 10 (see Table S.28).

higher σ^2_η, the smaller standard errors and corresponding confidence intervals. However, there is no case in which the measurement error correction overturns our conclusions from Table 4, suggesting that the null result is not driven by inflated standard errors due to measurement error in the dependent variable.

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