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ABSTRACT

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

Converging labor market opportunities of men and women have altered the economic incentives for how families invest monetary and time resources into the skill development of their children. In this paper, I study the causal impact of changes in the parental wage gap (PWG)—defined as the relative difference in 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 development as measured by their Big Five personality traits and externalizing/internalizing behaviors. This null effect can be rationalized by the offsetting effects of the PWG on monetary investments, i.e., more disposable household income that is increasingly controlled by mothers, and time investments, i.e., a substitution from in-home maternal care to informal childcare.

JEL Classification: 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 parents provide. 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 both mothers' and fathers' labor market incentives.[1] In many countries, these 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). Thus, 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 that links 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 psychological concepts such as emotional intelligence, locus of control, personality traits (e.g., conscientiousness), and preferences (e.g., risk aversion and patience).[2] Recent 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 labor market performance (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 for long-term life outcomes (Attanasio et al., 2020b; Sorrenti et al., forthcoming).

[1] 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).

[2] In economics, they are often considered as a residual dimension of skills that is not captured by standardized test scores (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 $5,555$ 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 for the potential hourly wages available to mothers and fathers in the labor market. 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 may 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, the measures of potential wages must be good proxies for mothers' and fathers' actual labor market incentives. Therefore, I show that intra-family changes in potential wages are highly predictive of intra-family changes in actual wages.

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: 1 SD increase in the potential wages of mothers (fathers) increases their working time by 1.2 (0.8) hours per day. For both mothers and fathers, these increases are mostly accounted for by reductions in personal time for hobbies and education. The amount of time devoted to childcare remains unaffected. Furthermore, I show that mothers and fathers react asymmetrically to changes in the potential wages of their partners. Fathers are generally unresponsive to the wage changes of mothers. Mothers, however, tend to substitute market work with childcare if the wages of their partners increase: a 1 SD increase in the potential wages of fathers decreases (increases) the mother's working time (childcare time) by 0.8 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 100% 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 0.5% (1%) per year for five (seven) 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 100% 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 100% decrease in the PWG increases the probability of using informal childcare by 0.05 points. Since informal childcare is considered 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 100% decrease in the PWG increases disposable household income by 1.63 Thsd. € per year and increases the total share of resources controlled by mothers by 4.07 percentage points. Since monetary resources are considered conducive to child development and mothers have a higher propensity to spend their money to the benefit of 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.

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., 2023, 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 difference between the median wages of full-time employed men and full-time employed 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 expanded from children aged three years and above to all children aged one year and above (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 rulers in the East encouraged female labor force participation through the early adoption of gender-equalizing policies, the West promoted a more traditional male-breadwinner model. Due to these diverging institutional regimes, 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.[3] 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 pre-

[3]See Almlund et al. (2011) and Borghans et al. (2008) for comprehensive overview articles. See also Table S.1 for short descriptions of each Big Five personality dimension.

dicts academic performance in fourth grade. The findings by 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 show sizable stability over the lifecycle, suggesting that changes to childhood personality may have lasting effects on an individual's long-term life outcomes (Baker et al., 2019; Fitzenberger et al., 2021; Roberts and DelVecchio, 2000). In the GSOEP, information on the Big Five of children is collected via a validated short scale administered to parents of children aged 2–3, 5–6, and 9–10 (Asendorpf and Van Aken, 2003; Weinert et al., 2007). The primary caretaker rates their child 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. 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 behavior, 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 18 questions related to five sub-scales (hyperactivity, emotional problems, prosocial behavior, conduct problems, and peer problems)—see Appendix Table S.2. The subscales 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.

The measures for the Big Five personality traits and externalizing and internalizing behaviours rely on subjective assessments of mothers. Therefore, one may worry that different reporting standards of mothers 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 the necessary data for this approach. Instead, I also consider more objective measures of child outcomes that are closely related to their 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.[4]

Parental investments. To study the pathways by which changes in the PWG influence children's socio-emotional skills, I construct indicators for the monetary and time investments that parents provide to their children.

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 on a typical day in a work week. I sum across both parents to measure 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

[4] 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.

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, 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 extended family, older siblings, friends, neighbors, 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 measured in 2015 prices.

Fourth, I consider the maternal share of household earnings as a measure of the amount of monetary resources controlled by the mother. 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).[5] The empirical strategy is based on a sibling design. Therefore, I further re-

[5] 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. According to this definition, I allow for non-biological family relationships and disregard

strict 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 lead to a higher likelihood of parental separation or a lower likelihood of having a sibling. In Supplementary Table S.4, I address such concerns by demonstrating that the PWG does not predict parental separation and maternal fertility in the following five years.

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 $5,555$ child-year observations and $2,546$ 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 20% 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.[6] Furthermore, 61% (29%) of children are exposed to non-parental formal (informal) childcare regularly. Mothers, on average, contribute 19% of household earnings, which reflects their lower rates of labor market participation and the continued existence of gender wage gaps in Germany (Appendix Figure S.1).

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.

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parents' marital status. In section 4.3, I show that my results remain unchanged when focusing on biological families or married parents only.

[6] In Appendix Table S.3, I compare the measure for childcare time in the GSOEP with different measures for childcare time in the German Time-Use Study (GTUS). The GTUS distinguishes between time investments into children 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=5,555; Sibling groups=2,546			
	Mean	SD	Min	Max
Panel (a): Child characteristics				
Female	0.49	0.50	0.00	1.00
Migration background	0.02	0.13	0.00	1.00
East Germany	0.20	0.40	0.00	1.00
Age	6.17	2.86	2.00	10.00
Birth rank	2.06	1.06	1.00	10.00
Panel (b): Child socio-emotional skills				
Openness	0.03	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	0.00	0.97	-3.31	2.08
Neuroticism	-0.02	0.98	-1.64	2.99
Externalizing	-0.12	0.96	-1.77	3.66
Internalizing	-0.10	0.98	-1.55	3.90
Panel (c): Parental investments				
Parental care (hours/day)	9.90	5.20	0.00	32.00
Formal care (yes/no)	0.61	0.49	0.00	1.00
Informal care (yes/no)	0.29	0.45	0.00	1.00
Total disp. family income (in Thsd. €)	46.05	25.95	6.54	568.49
Share maternal earnings (in %)	19.12	22.99	0.00	99.08

Data: GSOEP, SIAB, MZ.
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]).

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.[7] It contains a 2% random sample of Germans who are either employed, recipients of social benefits, or registered as job-seeking. It does not include self-employed workers and civil servants (Frodermann 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).[8] The data are organized in spells, allowing researchers to trace the

[7] I use the regional file SIAB-R 7519 which covers the period 1975–2019 and contains regional markers at the county level while cutting back on detail in other dimensions to preserve data confidentiality.

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

labor market biographies of individuals. I use information about an individual's establishment to aggregate employment spells to job cells where each observation 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. I observe daily wages for each job, the employment sector, and the job holder's socio-demographic characteristics.

The German Microcensus (MZ). The MZ is an annual household survey covering 1% of all German households and contains information on family socio-demographics, income, and living conditions (GESIS, 2020). In contrast to the SIAB, the MZ also contains 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).[9] As a result, I obtain a data set with $\approx 174,000$ job observations per year. I observe the working hours for each job, the employment sector, and the job holder'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:

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

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 constructed as a weighted average across wages paid in different sectors of the economy where weights are given by the historic employment exposure of groups to these sectors in 1995.

[9] Appendix Tables S.5 and S.6 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 job holders.

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 and 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 (Raumordnungsregionen). 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).[10] Second, I calculate sector-specific hourly wages in year t combining data from the SIAB and the MZ (Term [2] of equation 1). Specifically, I calculate average hourly wages paid in a sector s in year t by dividing the average daily wage (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.[11]

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.

[10] Appendix Tables S.7 and S.8 document the differential sorting of gender and education groups into industries and occupations in the base year 1995.

[11] 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.

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.

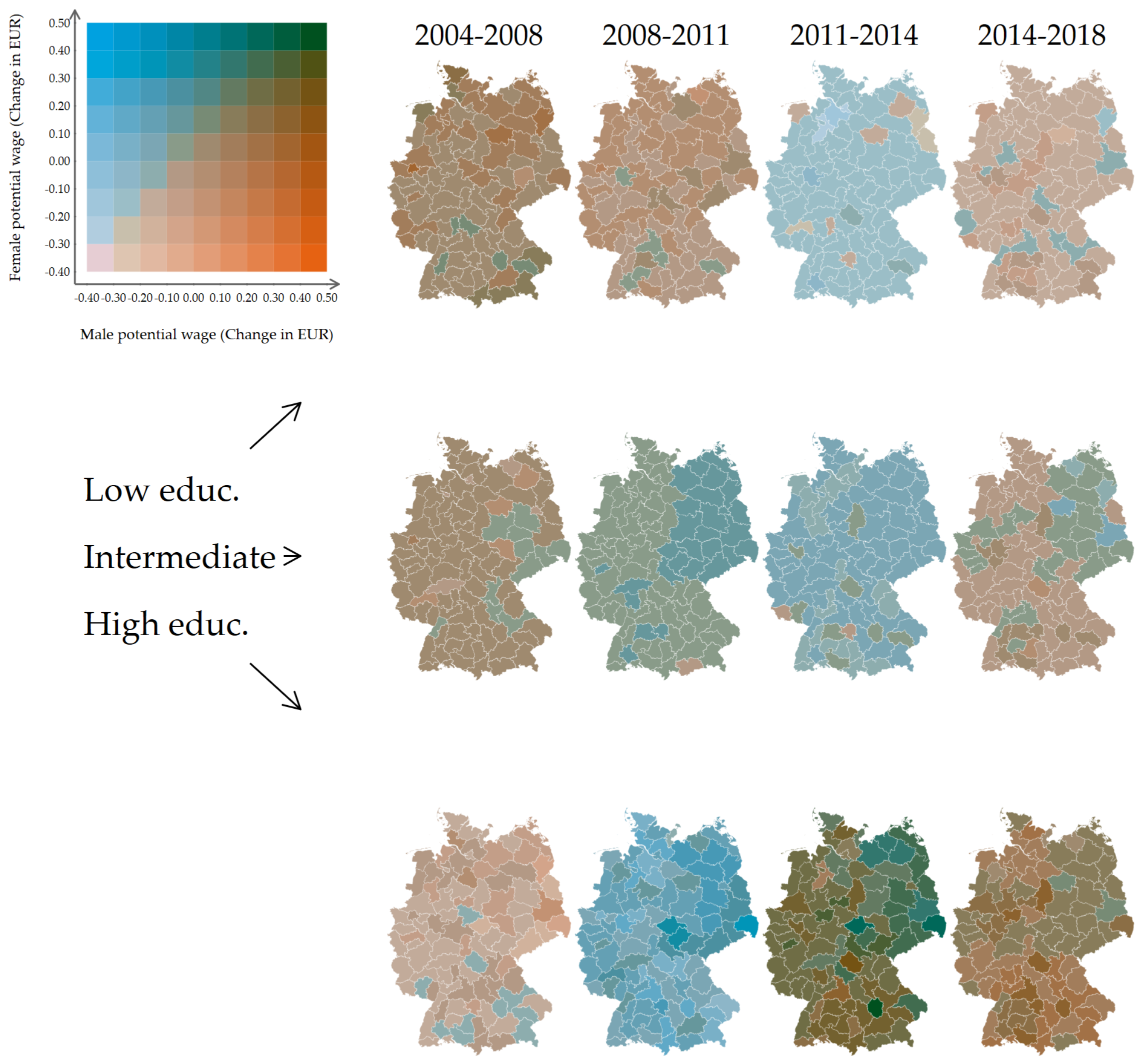
Consider the following ordinary least squares (OLS) regression:

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

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.

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

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*).

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 outcomes of interest and parental wages as well as reverse causality.

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

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

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, reflecting wage variation attributable to group-specific labor demand rather than to endogenous parental labor supply decisions, effectively address these concerns (Bartik, 1991).[12] 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 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 γ_{fa} and τ_t holds

[12] Shift-share (or Bartik) designs have become widely adopted in the literature strands 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).

the child's birth cohort and parental age constant and rules them out as confounding factors (Black et al., 2018; McGrath et al., 2014).

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

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

where $\hat{w}^{\Sigma}_{it-1}$ 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 biased when comparing them to standard errors based on alternative cluster definitions.

Identification assumption. The econometric properties of shift-share designs have been investigated in several recent methodological contributions (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.[13] 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

[13] Find in the following a restatement of equation 1 for easy reference:

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

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. 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 non-wage features that predict contemporaneous intra-family variation in children's socio-emotional skills.

I assess the plausibility of this identification assumption as follows. First, I illustrate that after conditioning on $\gamma_{f(i)a(it)}$ and τ_t, within-family differences in potential wages are uncorrelated with a large set of child characteristics that may predict their socio-emotional skills and parental investments. For this illustration, I restrict my analysis sample to sibling pairs, i.e., I exclude triplets and higher-order sibling groups. In turn, I assign siblings to a "high-shock" ("low-shock") group if their PWG at age a is higher (lower) than the corresponding PWG of their sibling. Panel (a) of Table 2 contrasts the "high-shock" and the "low-shock" groups in terms of their observable characteristics. Columns 1–3 show differences in observable characteristics after netting out family times child age fixed effects $\gamma_{f(i)a(it)}$ only. 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 "high-shock" 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

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

	N	Family × child age FE Low-shock (1)	Family × child age FE High-shock (2)	Family × child age FE Δ (3)	Family × child age FE + Year FE Low-shock (4)	Family × child age FE + Year FE High-shock (5)	Family × child age FE + Year FE Δ (6)
Panel (a): Sibling characteristics							
Female	4,300	0.479	0.488	0.009 (0.016)	0.481	0.489	0.008 (0.017)
Born before October	4,300	0.785	0.780	-0.004 (0.012)	0.784	0.780	-0.004 (0.014)
Birth year	4,300	2006.675	2007.373	0.699*** (0.070)	2007.723	2007.723	–
Firstborn	4,280	0.575	0.428	-0.147*** (0.019)	0.354	0.354	0.000 (0.014)
# of siblings	4,292	2.528	2.570	0.041*** (0.009)	2.602	2.594	-0.007 (0.009)
Birth height (cm)	2,242	50.823	50.921	0.098 (0.103)	50.974	50.972	-0.002 (0.109)
Birth weight (kg)	2,256	3.261	3.294	0.033* (0.018)	3.295	3.305	0.010 (0.018)
Days in hospital (3 months post-birth)	2,240	2.243	2.210	-0.033 (0.301)	2.037	2.141	0.104 (0.285)
Age (Mother)	4,300	35.990	36.688	0.699*** (0.070)	37.038	37.038	–
Age (Father)	4,300	39.276	39.978	0.702*** (0.071)	40.319	40.326	0.007 (0.013)
Panel (b): Treatment variables							
Potential wage (Father)	4,300	15.042	14.880	-0.162*** (0.017)	15.064	14.887	-0.177*** (0.016)
Potential wage (Mother)	4,300	13.878	13.912	0.034** (0.014)	13.880	13.913	0.033*** (0.006)
PWG	4,300	-1.164	-0.968	0.196*** (0.011)	-1.184	-0.975	0.209*** (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-shock* (*Low-shock*) group if they are subject to a lower (higher) 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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, providing the identifying variation on which I base my estimates.

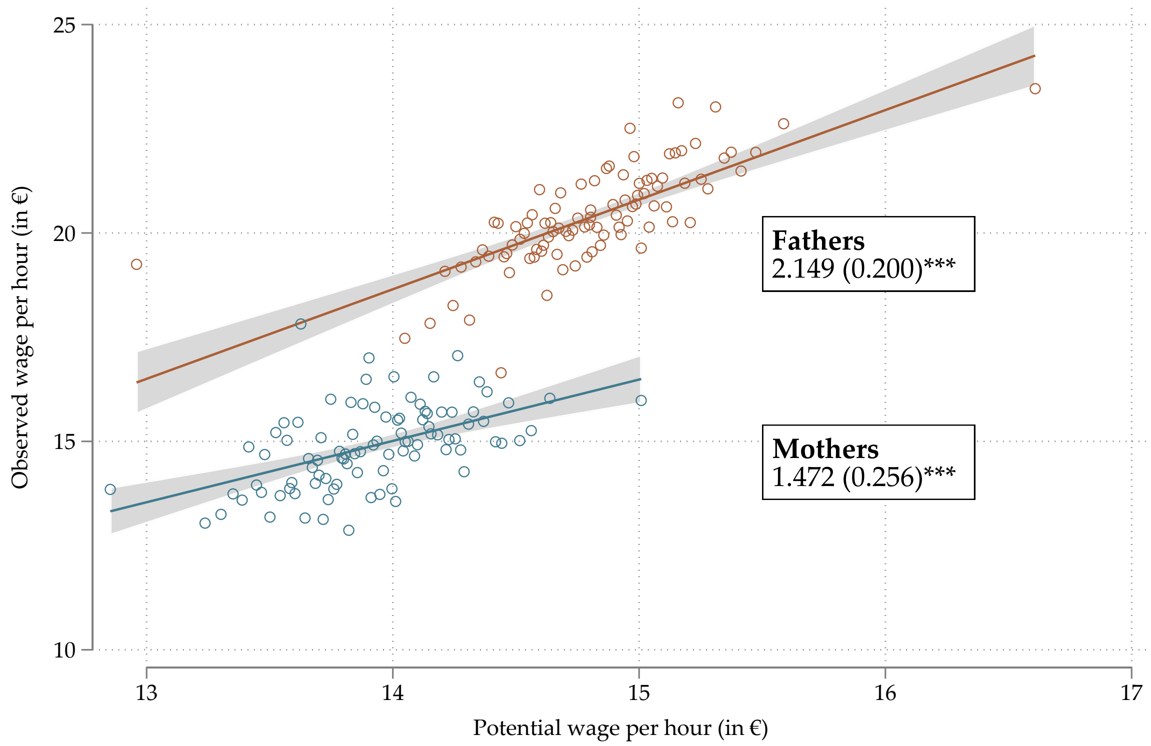
Second, I assess the sensitivity of my estimates to violations of the identification assumption concerning particular sectors of the economy. Goldsmith-Pinkham et al. (2020) show that shift-share estimates can be decomposed into just-identified, group-specific instrumental variable coefficients and their corresponding Rotemberg weights.[14] Rotemberg weights provide helpful indicators to make the origin of the identifying variation transparent and to illustrate for which sectors the identification assumptions have to hold to give the estimates a causal interpretation. 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.9 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 is accounted for by low-skill purchasing and sales occupations in wholesale and retail ($\approx$ 10%), low-skill logistics occupations in business services ($\approx$ 8%), and education and social care occupations ($\approx$ 7%). For fathers, most identifying variation is accounted for by 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 my estimates to sector-specific violations of the identification assumption stated in equation 5.

Lastly, I also 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 family times child age fixed effects. There is a strong correlation between intra-family changes in potential wages and observed wages for mothers and fathers. This result gives credence to the assumption that my 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

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

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



Data: GSOEP, SIAB, MZ.
Note: Own calculations. This figure shows the relationship between within-family changes in potential wages and within-family changes in observed wages for mothers and fathers. It is constructed from the core sample described in Table 1 by partialling out the family times child age fixed effect from actual and potential wages, respectively. Each data point reflects the average actual wage within a percentile bin of the gender-specific potential wage distribution. The solid lines indicate linear predictions across the gender-specific potential wage distribution. The gray shaded areas mark 95% confidence intervals.

changes in potential wages. These within-family 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 of the analysis 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 necessary 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.

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, and potential wages are standardized on the estimation sample to have a mean of zero and an SD of one.

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 1 SD ↑ in parental wages								
Mother	1.159*** (0.432)	-0.095 (0.524)	-0.217 (0.334)	-0.829*** (0.285)	-0.435 (0.566)	0.241 (0.372)	0.243 (0.258)	-0.354 (0.309)
Father	-0.806*** (0.258)	0.847** (0.402)	0.380 (0.234)	-0.087 (0.113)	0.746** (0.359)	0.240 (0.321)	0.021 (0.201)	-0.535** (0.254)
Family × child age FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
N	5,555	5,555	5,555	5,555	5,555	5,555	5,555	5,555
Outcome Mean	3.404	7.521	4.580	1.200	8.742	2.383	2.070	1.191
Outcome SD	3.461	4.270	2.233	1.294	3.207	2.413	1.767	1.386

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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Mothers have a positive own-wage elasticity of labor supply: a 1 SD increase in maternal potential wages increases maternal work time by 1.2 hours per day (Column 1). However, this increase in work for pay does not lead to major downward revisions in the time mothers allocate to childcare activities 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 1 SD increase in maternal potential wages decreases personal time by 0.8 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.[15] This conclusion is further supported by descriptive evidence from German time-use diaries. In Appendix Figure S.2, 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 in the number 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.

Fathers also have a positive but smaller own-wage elasticity of labor supply: a 1 SD increase in paternal potential wages increases paternal work time by 0.7 hours per day (Column 5). Thus, consistent with the estimates in Bargain et al. (2014), the labor supply of partnered men in Germany is approximately two-thirds as sensitive to wage variation as women's labor supply. Like mothers, their increased labor market activity is accounted for by decreased time for hobbies and education: a 1 SD increase in paternal potential wages decreases personal time by 0.5 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 1 SD increase in paternal potential wages decreases maternal working time by 0.8 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

[15] See Hsin and Felfe (2014) for similar results from the US.

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.[16] 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.

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). All outcomes and potential wages are standardized on the estimation sample to have a mean of zero and an SD of one.

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 1 SD increase in maternal potential wages increases children's extraversion by 0.26 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 0.02 to 0.16.

The lower panel of Table 4 displays the effect of the PWG on children's socio-emotional skills. The PWG is calculated as the difference in maternal and paternal potential wages. To isolate the effect of relative wages from the effects of wage levels, I control for the sum of maternal and paternal wages in all regressions (see equation 4). Coefficients are scaled to reflect a 100% decrease in the PWG. Therefore, the estimated coefficients answer a policy-relevant question:

[16] In Appendix Figure S.3, I use quantile regressions to show that the labor supply responses of mothers are driven by changes at both the extensive and the intensive margin. The labor supply responses of fathers are driven mainly by changes at the extensive margin, i.e., by transitions between unemployment and full-time employment.

Table 4 – Parental wages 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)
Panel (a): Effect of 1 SD ↑ in parental wages							
Mother	-0.134	0.094	0.263**	0.020	0.000	0.185	-0.081
	(0.130)	(0.138)	(0.110)	(0.118)	(0.187)	(0.211)	(0.163)
	[0.303]	[0.497]	[0.017]	[0.866]	[0.999]	[0.383]	[0.622]
	{0.970}	{0.995}	{0.159}	{1.000}	{1.000}	{0.990}	{1.000}
Father	-0.127	0.059	0.038	0.029	-0.003	-0.191	0.092
	(0.109)	(0.098)	(0.118)	(0.111)	(0.227)	(0.189)	(0.205)
	[0.245]	[0.546]	[0.745]	[0.791]	[0.990]	[0.315]	[0.653]
	{0.940}	{1.000}	{1.000}	{1.000}	{1.000}	{0.970}	{1.000}
Panel (b): Effect of 100% ↓ in average PWG							
PWG	-0.016	0.016	0.069*	0.001	0.001	0.083	-0.039
	(0.042)	(0.042)	(0.037)	(0.039)	(0.067)	(0.070)	(0.059)
	[0.696]	[0.699]	[0.063]	[0.987]	[0.994]	[0.237]	[0.514]
	{0.985}	{0.985}	{0.264}	{1.000}	{1.000}	{0.716}	{0.960}
Family × child age FE	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓
N	5,512	5,522	5,512	5,501	3,629	2,296	2,283

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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

what would be the average change in children's socio-emotional skills if we were to reduce the average PWG to zero?[17]

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

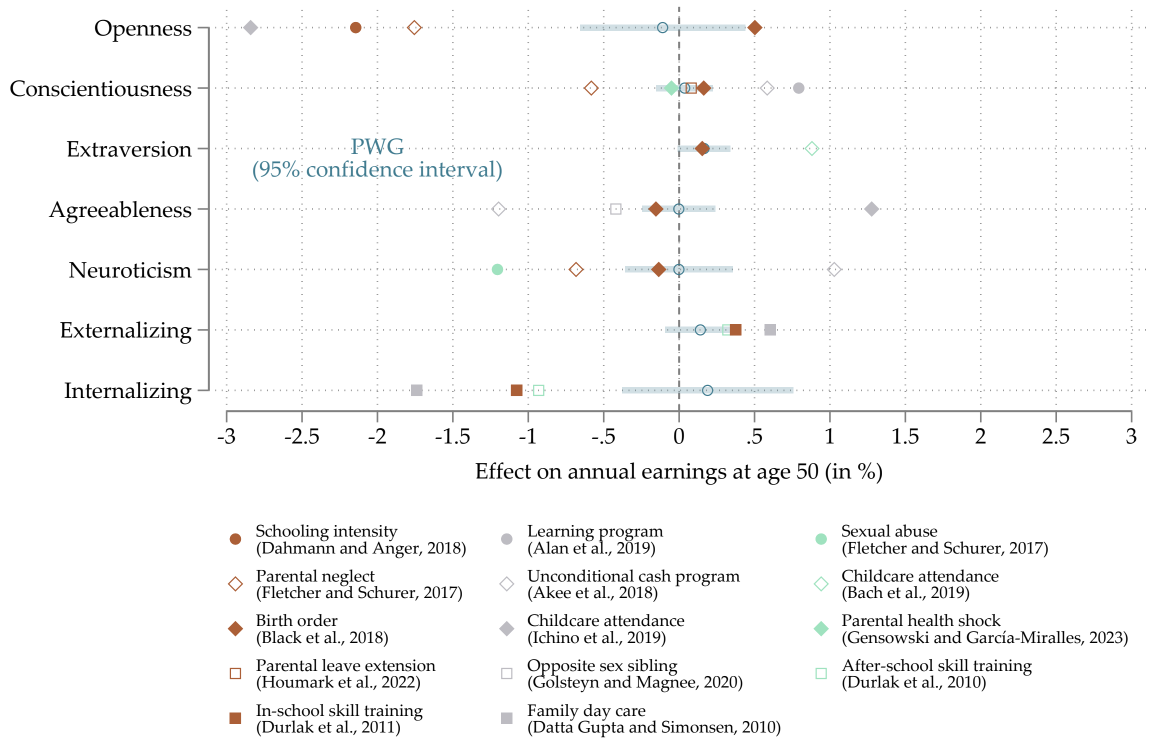
[17] The considered strength of this treatment is sizable. A 100% decrease in the PWG is equivalent to 124% of the change in the PWG over the entire investigation period (2005-2019). It is also equivalent to moving a child from the 25th percentile to the 56th percentile of the PWG distribution.

on extraversion is susceptible to alternative variable definitions, control variables, and sample restrictions (Appendix Table S.10).

Contextualizing effect sizes. Whether these null effects are informative depends on my study design's ability to rule out meaningful effect sizes. I assess the power of my research design in two steps. First, I calculate minimum detectable effect (MDE) sizes at 80% power. Appendix Figure S.4 shows the results of these power calculations: MDEs at sample sizes of $2,000$, $4,000$, and $6,000$ observations are 0.13, 0.09, and 0.07 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, neuroticism, and externalizing behavior, I can exclude earnings increases/decreases larger than 0.5% per year. For openness and internalizing behavior, I can exclude earnings increases/decreases that are larger than 1% per year. 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 effects 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 100% 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

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 100% 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 from column 3 of Table D.11 in Papageorge et al. (2019).

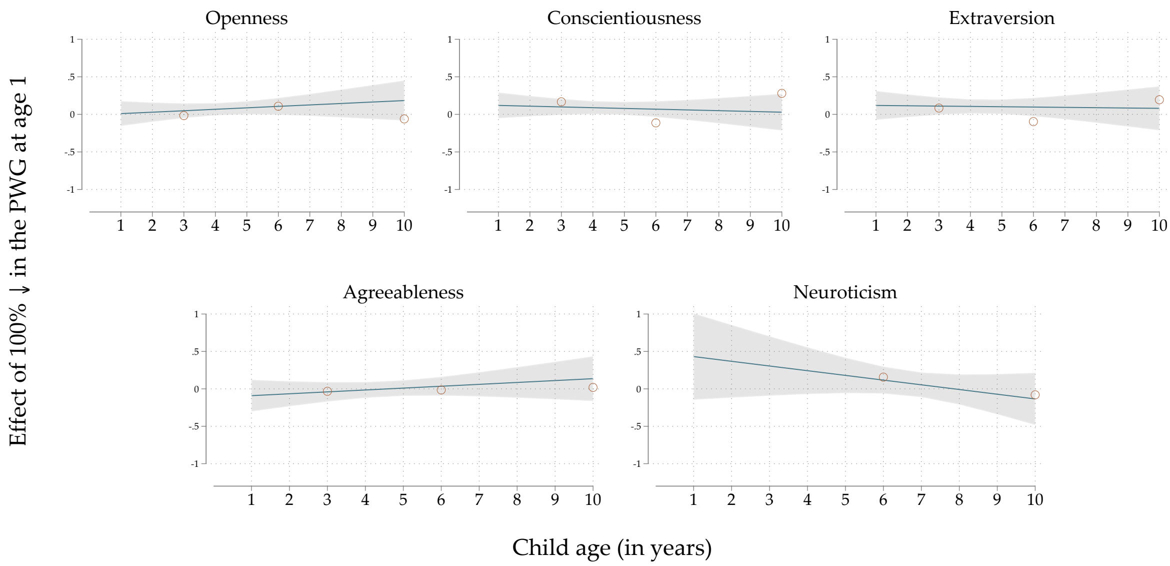
their long-term life outcomes.[18]

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. To investigate this possibility, I modify the baseline estimation as follows: I fix the PWG at child age one. 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. 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

[18]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 ten years. 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.

FIGURE 4 – Long-term effects of the PWG at age 1 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 100% decrease of the PWG at child age 1. 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 1-10. The gray shaded areas mark 95% confidence intervals. 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. Standard errors are clustered at the family level.

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 the increasing importance of early-life PWGs for children's socio-emotional skills until age 10. This finding further supports the interpretation that changes in the PWG do not instill consequences for the long-term life outcomes of children.[19]

Other outcomes. Furthermore, in Table 5, I show that the PWG does not affect other outcomes related to children's socio-emotional skills and long-term life outcomes.[20]

First, I consider children's BMI as a proxy for their health. Existing literature suggests that personality and externalizing/internalizing behaviors correlate strongly with the BMI (Attanasio

[19]Neuroticism seems to be an exception to this conclusion. However, neuroticism is first measured for children at age 6. Therefore, the estimated gradient relies on two data points only, and any projection for earlier child outcomes relies on strong extrapolation, as indicated by the wide confidence bands. For the same reason, I do not use externalizing/internalizing behavior in the long-run analysis.

[20]This sample differs from the core analysis sample. In particular, I do not restrict the sample regarding the availability of socio-emotional skill measures and parental investments to maximize the available sample size for this analysis.

TABLE 5 – Parental wages and other child outcomes

	BMI: Underweight (yes/no) (1)	BMI: Overweight (yes/no) (2)	Delayed school entry (yes/no) (3)	Upper secondary school track (yes/no) (4)
Effect of 1 SD ↑ in parental wages				
Mother	-0.010 (0.049)	-0.115 (0.079)	-0.106 (0.072)	-0.054 (0.078)
Father	0.064 (0.046)	-0.013 (0.033)	-0.014 (0.026)	0.014 (0.081)
Panel (b): Effect of 100% ↓ in average PWG				
PWG	-0.013 (0.015)	-0.029 (0.022)	-0.026 (0.019)	-0.017 (0.025)
Family × child age FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
N	5,115	5,115	5,106	8,734
Outcome Mean	0.117	0.262	0.094	0.513
Outcome SD	0.321	0.440	0.292	0.500

Data: GSOEP.
Note: Own calculations. This table shows changes in other child outcomes 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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). 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). Columns 1 and 2 of Table 5 show that we cannot reject the null hypothesis that the PWG has no impact on whether children are underweight or overweight, respectively.

Second, I consider the age of school entry as another proxy for potential 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 development concerning 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 after their scheduled school starting age. 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, students are tracked after primary school 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, the analysis of these alternative outcomes supports 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.10, I show the robustness of my findings to alternative ways of constructing potential wages for mothers and fathers.

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). My 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, my results are robust when using logarithmic transformations of maternal and paternal potential wages.

Alternative control variables. In Panel (b) of Appendix Table S.10, 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 for 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 non-wage features 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) separate 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 additional 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 intra-family changes in the availability and quality of public childcare slots. To address this concern, I show that results remain unchanged when adding separate 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.[21]

Alternative sample restrictions. In Panel (c) of Appendix Table S.10, I show the robustness of my findings to alternative sample restrictions.

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

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 only or (ii) married parents only.

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. 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 estimates except for a significant decrease in internalizing behavior at the 10%-level. However, this is the only specification where I find an effect of the PWG on internalizing behavior. Therefore, this single coefficient does not overturn the central conclusion that changes in the PWG do not affect children's socio-emotional skills in a meaningful way.

Alternative standard errors. In Appendix Table S.12, 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.

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 indicators for the monetary and time investments that parents provide to their children.

The upper panel of Table 6 displays the effects of maternal and paternal potential wages on parental investments. Potential wages are standardized on the estimation sample to have a mean of zero and an SD of one. The units of the investment variables are indicated in the corresponding column headers.

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 1 SD ↑ in parental wages					
Mother	0.146	-0.031	0.105*	5.434***	9.839**
	(0.560)	(0.067)	(0.056)	(1.918)	(4.128)
Father	1.087**	-0.033	-0.129**	-0.288	-7.002***
	(0.548)	(0.033)	(0.054)	(0.874)	(2.421)
Panel (b): Effect of 100% ↓ in average PWG					
PWG	-0.146	-0.003	0.053***	1.626***	4.068***
	(0.187)	(0.021)	(0.019)	(0.585)	(1.329)
Family × child age FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
N	5,555	5,555	5,555	5,555	5,555
Outcome Mean	9.904	0.611	0.292	46.046	19.124
Outcome SD	5.197	0.488	0.454	25.952	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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The results show that changes in maternal potential wages stimulate opposing forces on parents' time and monetary investments. A 1 SD increase in maternal potential wages neither affects the total care parents provide their children (Column 1) nor the probability of children enrolling in formal childcare (Column 2). However, it increases the probability that children are enrolled in informal childcare by 0.10 points (Column 3). This pattern echoes that mothers protect their overall time with children by increasing their engagement after work (see the discussion above). It also suggests that families substitute in-home care with informal childcare arrangements while mothers work. However, the labor supply responses of mothers also have substantial effects on the availability of monetary resources within households: a 1 SD increase in maternal potential wages increases total disposable family income by 5.43 Thsd. € (Column 4). It also increases the maternal share of earnings by 9.84 percentage points (Column 5).

Similarly, the effects of paternal potential wages on parental investments are also ambiguous. A 1 SD increase in paternal potential wages increases the total amount of time parents devote to childcare by 1.09 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 0.13 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 their partners' decreased labor market activity (see Table 3). However, the increased earnings of fathers and decreased earnings of mothers lead to a 7.00 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 100% 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 100% decrease in the PWG increases the probability of using informal childcare by 0.05 points (Column 3), increases disposable household income by 1.63 Thsd. € per year (Column 4), and increases the total share of resources controlled by mothers by 4.07 percentage points (Column 5).

The effects of maternal and paternal potential wages on parental investments illustrate why a decline in the PWG leads to significant changes in children's living environments without negatively impacting their socio-emotional development. Regarding time investments, existing literature shows that 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. Thus, my 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.11, I show the robustness of the effects of the PWG on parental investments 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.12.

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 that are motivated by evidence from the existing literature: 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 subscales 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.[22]

Table 7 presents the results for a 100% decrease in the PWG on children's socio-emotional skills for different population subgroups. Effects are estimated by interacting the PWG with the binary indicators displayed in the table headers. In all regressions, I control for family times child age fixed effects $\gamma_{f(i)a(it)}$, time fixed effects τ_t, as well as the sum of maternal and paternal wages (interacted with the corresponding heterogeneity variable) to isolate the heterogeneous effect of relative earnings potentials from the effects of wage levels.

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: uniformly decreasing the PWG by 100% decreases the personality factor of older children ($>$ 6 years) by 0.14 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. In Appendix Table S.14, I show 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 negative effect of increased informal childcare is less counterbalanced by in-

[22]In Appendix Table S.13, I show how both indexes relate to disaggregated measures of socio-emotional skills. The "personality factor" relates positively to openness, conscientiousness, extraversion, and agreeableness and negatively to neuroticism. The "total difficulty score" relates positively to externalizing and internalizing behavior.

Table 7 – Heterogeneity: Effect of 100% ↓ in the PWG on children's socio-emotional skills by subgroup

Panel (a): Effect of 100% ↓ in average PWG on Personality Factor

Child sex			Birth order			Child age		
Male	Female	Diff.	First	Higher	Diff.	≤ 6	> 6	Diff.
0.011	0.029	0.018	0.021	0.020	-0.001	0.054	-0.088	-0.142*
(0.041)	(0.041)	(0.016)	(0.040)	(0.042)	(0.014)	(0.041)	(0.072)	(0.075)
Region of residence			**Education (Mother)**			**Poverty**		
West	East	Diff.	Low	High	Diff.	$\leq$ P25	$>$ P25	Diff.
0.041	-0.009	-0.050	-0.078	0.022	0.100	0.020	0.032	0.013
(0.047)	(0.073)	(0.089)	(0.073)	(0.050)	(0.073)	(0.040)	(0.043)	(0.022)

Panel (b): Effect of 100% ↓ in average PWG on Total Difficulty Score

Child sex			Birth order			Child age		
Male	Female	Diff.	First	Higher	Diff.	≤ 6	> 6	Diff.
0.025	0.039	0.014	0.048	0.047	-0.001	0.015	0.095	0.080
(0.055)	(0.057)	(0.021)	(0.053)	(0.057)	(0.020)	(0.056)	(0.107)	(0.106)
Region of residence			**Education (Mother)**			**Poverty**		
West	East	Diff.	Low	High	Diff.	$\leq$ P25	$>$ P25	Diff.
0.105*	-0.056	-0.162**	0.025	-0.040	-0.065	0.030	-0.008	-0.038
(0.057)	(0.064)	(0.071)	(0.102)	(0.068)	(0.083)	(0.055)	(0.068)	(0.038)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in children's socio-emotional skills in response to a 100% 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

creased 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: uniformly decreasing the PWG by 100% increases the total difficulty score of children in the West by 0.16 SD more than of children in the East. We can again link this finding back to the heterogeneous effects of the PWG on parental investments. In Appendix Table S.15, I show 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, the results of this analysis suggest that the limited 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 do not 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 development. 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 family policy. However, these goals are often thought to conflict with each other.[23] In contrast to such concerns, the evidence presented in this study suggests that strides toward gender equality do not necessarily imply adverse effects on the socio-emotional development of the next generation.

[23] 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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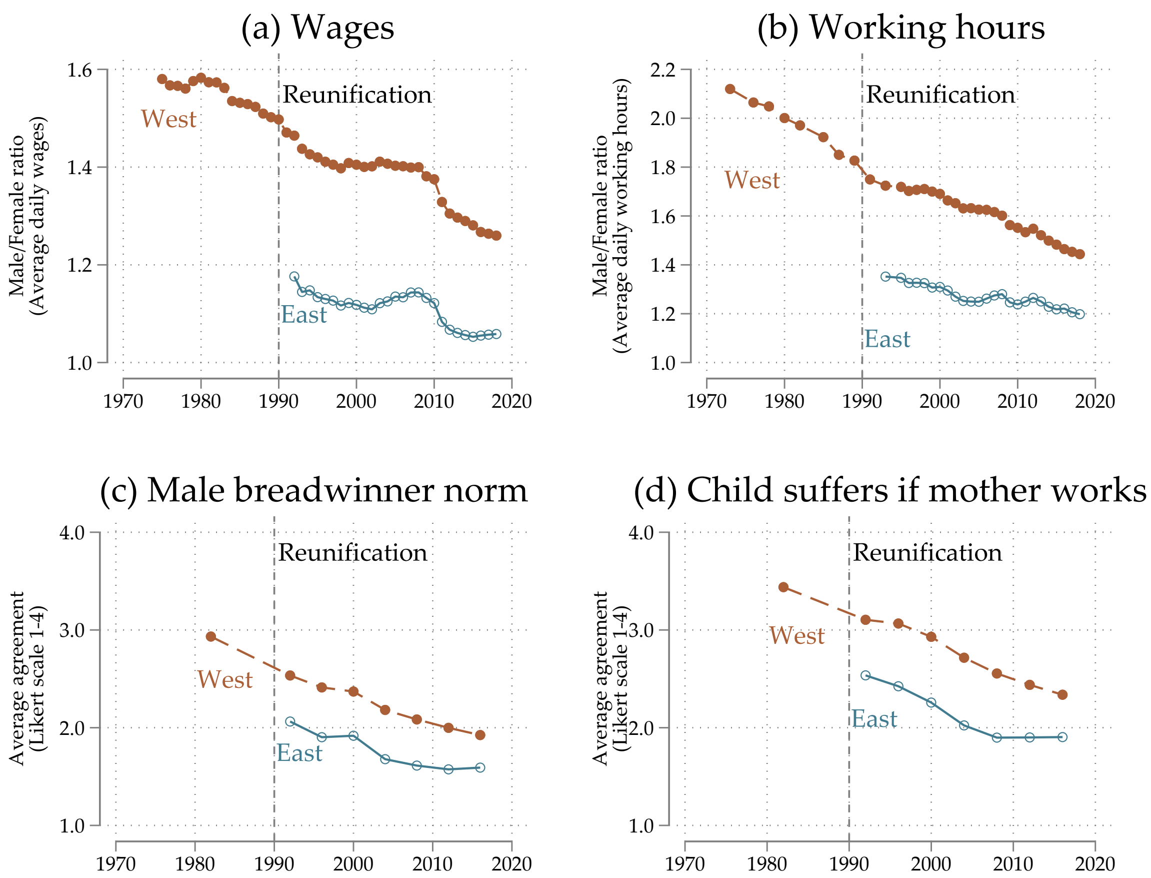
The Parental Wage Gap and the Development of Socio-emotional Skills in Children

Paul Hufe

Supplementary Material
May 2, 2024

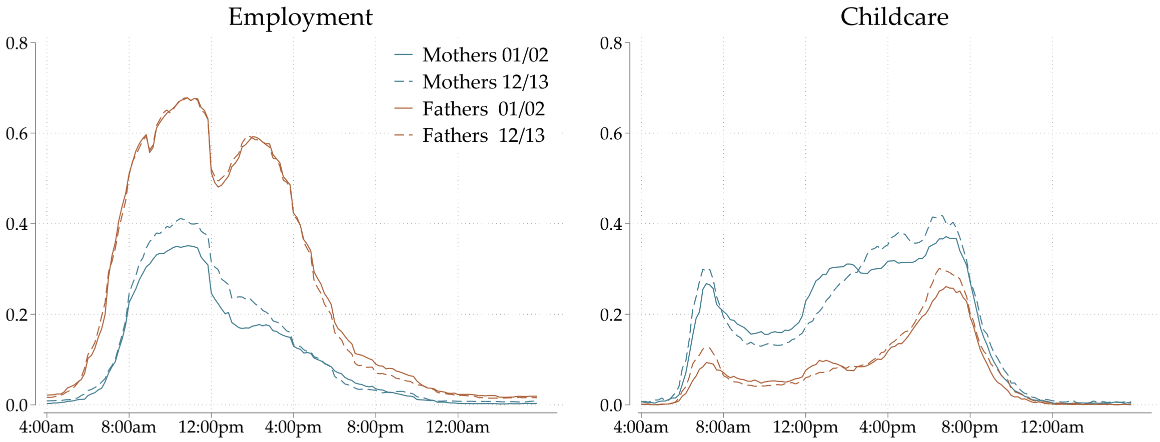
A ADDITIONAL FIGURES

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



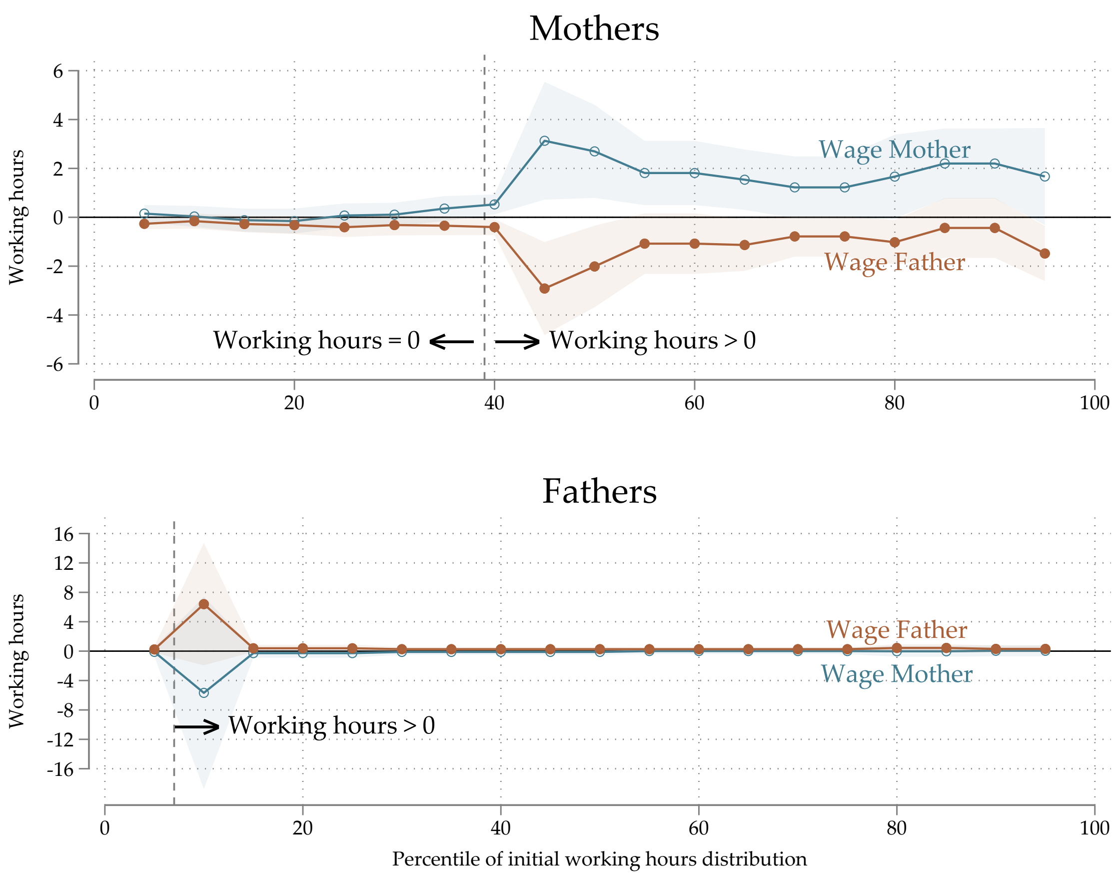
Data: SIAB, MZ, ALLBUS.
Note: Own calculations. Panel (a) shows the male-to-female ratio in mean daily wages from 1975 to 2019. Daily wages are calculated for all SIAB observations aged 18–63 that are subject to social security contributions. Panel (b) shows the male-to-female ratio in daily working 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 – Time-use of mothers and fathers in Germany, 2001/02 and 2012/13



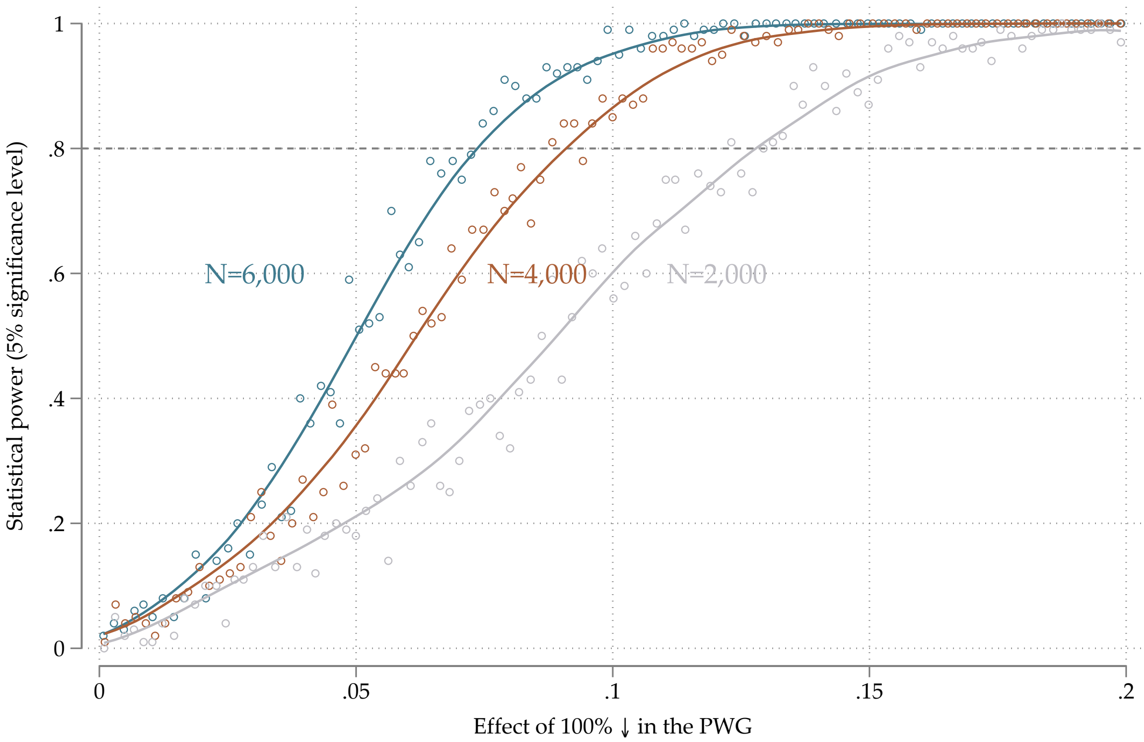
Data: GTUS.
Note: Own calculations. This figure shows the share of mothers and fathers involved in employment and childcare activities for each 10-minute time window of the day. The samples include two-parent households aged 18–63 with at least one resident child below age 17. All variables refer to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

FIGURE S.3 – Impact of a 1 SD 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 1 SD 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. 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.4 – 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 $\mathcal{N} = (0.00, 0.33)$. These specifications correspond to Openness and the PWG (rescaled to represent a 100% decrease) 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, 0.20]. 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 – 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.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 1 SD ↑ in parental wages				
Mother	0.053 (0.039)	0.006 (0.013)	0.035 (0.059)	-0.017 (0.028)
Father	0.011 (0.017)	0.002 (0.005)	-0.073* (0.044)	-0.006 (0.015)
Panel (b): Effect of 100% ↓ in average PWG				
PWG	0.013 (0.012)	0.002 (0.006)	0.023 (0.019)	-0.004 (0.013)
Family × child age FE	✓	×	✓	×
First differences	×	✓	×	✓
Year FE	✓	✓	✓	✓
N	5,555	4,234	5,543	3,796
Outcome Mean	0.036	0.023	0.128	-0.136
Outcome SD	0.187	0.161	0.334	0.363

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 – 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.6 – 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.7 – 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.8 – 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.9 – 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	10.36%	7.52	[3.50,12.00]
Logistics Occ. (Low) in Information/Communication/Business Services	0.08	7.89%	2.86	[-2.50,5.50]
Education/Social Care Occ. (All) in Education	0.07	7.16%	6.71	[2.50,11.50]
Administrative Occ. (All) in Finance/Insurance	0.05	4.93%	5.79	[-6.50,15.00]
Logistics Occ. (Low) in Human Health Services	0.04	4.30%	5.17	[0.50,8.00]
Commodity Prod. Occ. (All) in Manufacturing: Food/Textiles	0.03	3.13%	8.45	[5.50,14.50]
Medical Care Occ. (Low) in Human Health Services	0.03	2.85%	9.55	[-0.50,30.00]
Medical Care Occ. (High) in Human Health Services	0.03	2.63%	-1.08	[-25.00,10.00]
Logistics Occ. (Low) in Wholesale/Retail	0.03	2.60%	6.72	[3.50,10.00]
Purchasing/Sales (Low) in Manufacturing: Food/Textiles	0.03	2.58%	8.34	[3.50,14.00]
Panel (b): Fathers				
Machine-Building Occ. (High) in Manufacturing: Electronics/Vehicles/Machinery	0.18	17.37%	1.11	[-0.50,3.00]
Construction Occ. (Low) in Construction	0.11	10.86%	2.30	[1.00,3.50]
Science/IT Occ. (High) in Information/Communication/Business Services	0.04	4.35%	1.49	[0.00,3.00]
Administrative Occ. (All) in Manufacturing: Electronics/Vehicles/Machinery	0.04	4.26%	1.20	[-0.50,3.00]
Logistics Occ. (Low) in Transportation/Storage	0.04	4.16%	2.15	[0.00,4.50]
Machine-Building Occ. (High) in Information/Communication/Business Services	0.03	3.22%	2.50	[1.00,4.00]
Medical Care Occ. (High) in Human Health Services	0.03	2.55%	-0.08	[-4.00,3.50]
Logistics Occ. (Low) in Information/Communication/Business Services	0.03	2.54%	2.02	[-1.50,6.50]
Administrative Occ. (All) in Finance/Insurance	0.03	2.52%	2.99	[-1.00,11.50]
Raw Material Processing Occ. (Low) in Manufacturing: Raw Materials/Metals/Chemicals	0.03	2.50%	3.45	[1.00,6.50]

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.10 – Robustness: 100% decrease in the PWG and socio-emotional skills

	Big Five Personality Traits					SDQ	
	Open-ness (1)	Conscientious-ness (2)	Extra-version (3)	Agreeable-ness (4)	Neuro-ticism (5)	External-izing (6)	Internal-izing (7)
Baseline	-0.016 (0.042)	0.016 (0.042)	0.069* (0.037)	0.001 (0.039)	0.001 (0.067)	0.083 (0.070)	-0.039 (0.059)
Panel (a): Alternative construction of potential wages							
No imputation	-0.015 (0.031) [5,512]	0.014 (0.031) [5,522]	0.047 (0.029) [5,512]	-0.006 (0.029) [5,501]	0.010 (0.052) [3,629]	0.065 (0.056) [2,296]	-0.025 (0.048) [2,283]
CPS imputation	-0.020 (0.040) [5,512]	0.016 (0.040) [5,522]	0.061* (0.035) [5,512]	-0.004 (0.037) [5,501]	0.005 (0.065) [3,629]	0.082 (0.068) [2,296]	-0.036 (0.057) [2,283]
Updating (Shenhav, 2021)	-0.011 (0.040) [5,512]	0.014 (0.040) [5,522]	0.064* (0.035) [5,512]	-0.003 (0.037) [5,501]	0.007 (0.064) [3,629]	0.082 (0.068) [2,296]	-0.033 (0.055) [2,283]
Updating ($t-10$)	0.004 (0.040) [5,512]	0.027 (0.040) [5,522]	0.071* (0.038) [5,512]	0.003 (0.038) [5,501]	-0.053 (0.069) [3,629]	0.030 (0.063) [2,296]	-0.031 (0.059) [2,283]
Log differences	-0.024 (0.035) [5,512]	0.004 (0.034) [5,522]	0.038 (0.030) [5,512]	0.001 (0.031) [5,501]	0.023 (0.056) [3,629]	0.052 (0.061) [2,296]	-0.002 (0.047) [2,283]
Panel (b): Alternative control variables							
Child characteristics	-0.016 (0.042) [5,474]	0.010 (0.042) [5,484]	0.068* (0.037) [5,474]	0.014 (0.040) [5,463]	0.022 (0.063) [3,606]	0.089 (0.068) [2,276]	-0.032 (0.066) [2,265]
Formal childcare availability & quality	-0.024 (0.042) [5,331]	0.005 (0.043) [5,341]	0.076** (0.037) [5,331]	-0.001 (0.039) [5,320]	-0.002 (0.067) [3,629]	0.101 (0.070) [2,296]	-0.028 (0.061) [2,283]
CZ trends	-0.041 (0.045) [5,512]	-0.017 (0.047) [5,522]	0.047 (0.041) [5,512]	-0.035 (0.044) [5,501]	0.001 (0.074) [3,629]	0.085 (0.073) [2,295]	-0.108* (0.062) [2,282]
Education trends	-0.002 (0.044) [5,512]	-0.007 (0.047) [5,522]	0.039 (0.038) [5,512]	-0.011 (0.041) [5,501]	-0.015 (0.066) [3,629]	0.080 (0.074) [2,296]	-0.014 (0.050) [2,283]
Panel (c): Alternative sample restrictions							
Married parents	0.008 (0.045) [5,015]	0.034 (0.046) [5,026]	0.087** (0.043) [5,018]	0.016 (0.043) [5,008]	-0.012 (0.075) [3,366]	0.084 (0.075) [2,130]	-0.028 (0.062) [2,118]
Biological parents	-0.018 (0.042) [5,481]	0.014 (0.042) [5,491]	0.070* (0.037) [5,481]	-0.002 (0.039) [5,470]	0.002 (0.067) [3,604]	0.087 (0.070) [2,277]	-0.035 (0.058) [2,264]
Within-child estim.	0.003 (0.028) [3,767]	-0.011 (0.030) [3,766]	0.017 (0.025) [3,763]	0.001 (0.028) [3,751]	-0.007 (0.036) [1,583]	0.031 (0.051) [993]	-0.093* (0.050) [992]

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows robustness checks for changes in children's socio-emotional skills in response to a 100% 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.11 – Robustness: 100% 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	-0.146 (0.187)	-0.003 (0.021)	0.053*** (0.019)	1.626*** (0.585)	4.068*** (1.329)
Panel (a): Alternative construction of potential wages					
No imputation	-0.082 (0.141) [5,555]	-0.001 (0.016) [5,555]	0.043*** (0.015) [5,555]	1.184*** (0.436) [5,555]	3.067*** (0.996) [5,555]
CPS imputation	-0.140 (0.176) [5,555]	-0.007 (0.021) [5,555]	0.054*** (0.019) [5,555]	1.515*** (0.564) [5,555]	3.953*** (1.313) [5,555]
Updating (Shenhav, 2021)	-0.123 (0.172) [5,555]	-0.004 (0.020) [5,555]	0.052*** (0.018) [5,555]	1.569*** (0.561) [5,555]	3.835*** (1.297) [5,555]
Updating ($t-10$)	-0.150 (0.186) [5,555]	-0.005 (0.020) [5,555]	0.049*** (0.019) [5,555]	1.427*** (0.532) [5,555]	3.233*** (1.232) [5,555]
Log differences	-0.173 (0.160) [5,555]	-0.006 (0.019) [5,555]	0.046*** (0.016) [5,555]	1.192** (0.487) [5,555]	3.719*** (1.202) [5,555]
Panel (b): Alternative control variables					
Child characteristics	-0.065 (0.181) [5,515]	-0.006 (0.021) [5,515]	0.048** (0.019) [5,515]	1.735*** (0.600) [5,515]	4.034*** (1.328) [5,515]
Formal childcare availability & quality	-0.157 (0.189) [5,374]	-0.001 (0.021) [5,374]	0.052*** (0.019) [5,374]	1.623*** (0.593) [5,374]	4.079*** (1.350) [5,374]
CZ trends	-0.336* (0.204) [5,555]	-0.014 (0.018) [5,555]	0.049** (0.023) [5,555]	2.034*** (0.688) [5,555]	4.061*** (1.245) [5,555]
Education trends	-0.178 (0.202) [5,555]	0.011 (0.020) [5,555]	0.054** (0.021) [5,555]	1.295** (0.593) [5,555]	3.064** (1.200) [5,555]
Panel (c): Alternative sample restrictions					
Married parents	-0.088 (0.207) [5,059]	0.006 (0.024) [5,059]	0.063*** (0.023) [5,059]	1.723** (0.696) [5,059]	4.267*** (1.470) [5,059]
Biological parents	-0.127 (0.185) [5,524]	-0.003 (0.021) [5,524]	0.053*** (0.019) [5,524]	1.597*** (0.581) [5,524]	4.040*** (1.326) [5,524]
Within-child estim.	0.109 (0.134) [4,234]	0.011 (0.012) [4,234]	0.002 (0.014) [4,234]	1.110*** (0.346) [4,234]	2.902*** (0.871) [4,234]

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows robustness checks for changes in parental investments in response to a 100% 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.12 – Tests for appropriate level of clustering

	No clustering	Clustering by ... Educ. (M.) × Educ. (F.) × CZ	Educ. (M.)	Educ. (F.)	CZ
	(1)	(2)	(3)	(4)	(5)
Panel (a): Big Five Personality Traits					
Openness	2.891 [0.002]	0.549 [0.291]	0.087 [0.465]	-0.922 [0.822]	0.460 [0.323]
Conscientiousness	2.967 [0.002]	-0.485 [0.686]	-1.065 [0.857]	-0.891 [0.813]	-0.658 [0.745]
Extraversion	4.734 [0.000]	-0.088 [0.535]	-1.046 [0.852]	-0.759 [0.776]	2.070 [0.019]
Agreeableness	3.670 [0.000]	-1.109 [0.866]	-0.073 [0.529]	-0.355 [0.639]	-0.460 [0.677]
Emotional stability	3.465 [0.000]	0.757 [0.225]	-0.424 [0.664]	-0.899 [0.816]	1.704 [0.044]
Panel (b): Strength and Difficulty Questionnaire					
Externalizing behavior	2.903 [0.002]	1.424 [0.077]	-1.235 [0.892]	-0.059 [0.523]	1.897 [0.029]
Internalizing behavior	3.567 [0.000]	0.319 [0.375]	0.812 [0.208]	-1.142 [0.873]	0.335 [0.369]
Panel (c): Parental Investments					
Parental care	2.474 [0.007]	-1.567 [0.941]	-0.983 [0.837]	-0.267 [0.605]	-1.461 [0.928]
Formal care (yes/no)	2.811 [0.002]	2.037 [0.021]	-0.429 [0.666]	0.087 [0.465]	2.008 [0.022]
Informal care (yes/no)	4.779 [0.000]	-1.005 [0.842]	-1.086 [0.861]	-0.778 [0.782]	-0.784 [0.783]
Total disp. family income (in Thsd. €)	2.488 [0.006]	1.326 [0.092]	-0.456 [0.676]	0.813 [0.208]	0.932 [0.176]
Share maternal earnings (in %)	2.671 [0.004]	-1.511 [0.935]	0.650 [0.258]	-0.477 [0.683]	-0.704 [0.759]

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 of the table 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.13 – Decomposition of Personality Factor and Total Difficulty Score

	Personality Factor (1)	Total Difficulty Score (2)
Openness	0.489*** (0.002)	–
Conscientiousness	0.348*** (0.002)	–
Extraversion	0.312*** (0.002)	–
Agreeableness	0.326*** (0.002)	–
Neuroticism	-0.019*** (0.002)	–
Externalizing behavior	–	0.682*** (0.002)
Internalizing behavior	–	0.484*** (0.002)
N	3,622	2,751
Outcome Mean	0.009	0.000
Outcome SD	0.999	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. Significance levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

TABLE S.14 – 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 100% ↓ in average PWG	-0.205 (0.202)	0.057 (0.329)	-0.010 (0.018)	0.016 (0.053)	0.043** (0.020)	0.087*** (0.029)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	≤ 6	> 6	≤ 6	> 6
Effect of 100% ↓ in average PWG	2.118*** (0.599)	-0.002 (0.962)	3.226*** (1.209)	6.860*** (2.164)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 100% 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.15 – 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 100% ↓ in average PWG	-0.363	0.089	0.003	-0.017	0.065***	0.030
	(0.237)	(0.218)	(0.020)	(0.027)	(0.024)	(0.024)

Panel (b): Monetary investments

	Total disp. family income (income in Thsd. €)		Share maternal earnings (in %)	
	West	East	West	East
Effect of 100% ↓ in average PWG	1.915**	1.426**	3.718***	4.295**
	(0.766)	(0.608)	(1.320)	(1.906)

Data: GSOEP, SIAB, MZ.
Note: Own calculations. This table shows changes in parental investments in response to a 100% 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: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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