Beliefs on Children's Human Capital Formation and Mothers at Work*

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Abstract

Mothers may face pressure to sort out of the labor market due to perceptions that women have an absolute advantage in child-rearing, even when their earnings potential matches that of men. Guided by a simple model, we use a survey experiment where we equalize earnings potential across gender and show that women are perceived to hold an absolute advantage in child-rearing. We then experimentally test mechanisms underlying these beliefs, finding that mothers are expected to spend more time on skill investments with their children than fathers who have equivalent time available. Finally, we find that when mothers work full-time, children's actual performance is generally underestimated, but providing factual information about their outcomes, leads to more accurate beliefs and reduced expectations of harm to the child. Our results show that beliefs about an absolute advantage for women in child-rearing are indeed present and highlight the need for targeted interventions to address misinformation about children's outcomes when mothers pursue careers.

JEL-Codes: D13, D83, J16, J22

Keywords: motherhood penalty, absolute advantage, belief elicitation, information

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1 Introduction

Across North America and Europe, mothers experience a 25–30% drop in employment after childbirth (Kleven et al., 2023), a penalty that remains resistant to policy interventions (Kleven et al., 2024). Lower earnings for women relative to men are wide-spread and well documented (Bertrand, 2011, 2020; Goldin, 2006), becoming particularly pronounced for new mothers (Kleven et al., 2019). Economic theory offers two explanations related to child-rearing. One is that women have a lower earnings potential than men in the labor market, leading to a comparative advantage in child-rearing (Becker, 1985). However, the persistence of gender pay gaps within firms and for highly skilled women suggests alternative explanations (Blau and Kahn, 2017; Card et al., 2016). Another is that traditional gender norms mean women are believed to have an absolute advantage in child-rearing relative to men (Cortés et al., 2022). Consider, for instance, a policy that reduces gender discrimination in hiring and promotions. Even if successful in equalizing earnings potential across genders, these beliefs may still pressure women to contribute less to the labor market.

Beliefs on absolute advantage are then important for understanding gender gaps and policy design. However, it is not straightforward to measure them. They can be obscured by many combinations of preferences (Manski, 2004) or by differences in earnings potential. This difficulty leaves the empirical relevance of beliefs on absolute advantage an open question. Additionally, the presence of these beliefs will suggest the need for policies that are informative about how well children do when mothers maintain careers to reduce uncertainty and misinformation, but whether information can really nudge beliefs about children's outcomes when mothers work is unclear.

In this paper, we address beliefs about how well children do when mothers maintain careers. Our model demonstrates that both comparative and absolute advantage lead women to spend more time at home. Importantly, beliefs that women hold an absolute advantage in child-rearing imply that policies equalizing earnings potential will not be sufficient to close motherhood penalties, while observing labor supply itself, does not reveal whether women are perceived to have an absolute advantage. We use our model to define a distribution of beliefs on absolute advantage by comparing expectations of a child's future human capital accumulation when a mother works long hours in the labor market *versus* a father, assuming their earnings potential is equalized. Motivated by this target belief distribution, we develop a component of our survey to estimate these beliefs.

We start with our first of four contributions by introducing a new survey design to elicit beliefs on absolute advantage. We run our survey with parents in England recruited through Prolific. Participants are presented with vignettes where we pin down the earnings potential across a mother and father and vary which parent works longer hours in the labor market. Each participant views three scenarios in which the mother works longer hours and three in which the father does. In each set, we iterate the wage of the parent working longer hours in exactly the same way and elicit participants' expectations on the hypothetical child's likelihood of graduating from university and their earnings rank at age 30.

This design allows us to estimate how beliefs on children's future outcomes change within-individuals when mothers work long hours relative to fathers with an equalized earnings potential. Our first contribution, Result 1 in Section 3.3, is that, on average, people expect worse outcomes for children when mothers work long hours relative to fathers. Participants significantly reduce the expected likelihood of graduation by just under 1% and earnings rank by 0.67 percentiles. While these magnitudes are not large, they demonstrate that even with the uncertainty of earnings differentials removed, beliefs on absolute advantage persist.

Second, we aggregate expectations at the individual-level to extract an individual-specific measure of these beliefs. We then assess how beliefs vary by participants' background, including information on the employment history of their own-mother, and their own experience of the motherhood penalty (for women only), which we construct from life histories. We find that the role model effect from participants seeing their own-mother work full-time while they were young fully wipes out beliefs on absolute advantage (Result 2, Section 3.4). This reinforces a literature on the inter-generational transmission of gender norms (Alesina et al., 2013; Fernández and Fogli, 2009) and shows that they shape perceptions on mothers' absolute advantage in child-rearing consistent with a theory of family narratives shaping children's eventual beliefs in adulthood (Akerlof and Rayo, 2020). Additionally, among women, beliefs about absolute advantage are strongest for those who experienced the highest post-birth employment penalties, strengthening the case that norms relate to the degree of motherhood penalties (Boinet et al., 2024).[1]

Third, we study mechanisms that can give rise to variation in beliefs about absolute advantage and help explain the mental models people hold. Specifically, we highlight three key dimensions that may shape this distribution of beliefs. First, people may expect *differences in preferences*, believing that even with equal time available, men are less likely than women to allocate time toward investments into children's skills. Second, people may hold expectations on the *productivity of time investments*, where they perceive mothers as more productive than fathers for an equal amount of time spent on investments. Third, people may hold expectations on *resource allocation*, where they expect mothers to allocate more resources to skill investments. If mothers are expected to have more resource control as they earn a higher share of the household budget, then this expectation would work to offset the beliefs on absolute advantage we just outlined. Further, we

[1] From life histories, we esitmate the motherhood employment penalty for women in our sample, showing in the Appendix, Section D.1.3 that mothers in our sample have experienced a very similar penalty as documented in the literature by Kleven et al. (2023).

consider an additional possibility that beliefs may be obscured by differing expectations on parental skills when, in our vignettes, a mother *versus* a father increases their time at work.

To study whether any of these mental mappings matter, we introduce a new series of vignettes and randomize features across participants. The specific details are described in Section 3.5 and the evidence is summarized by Result 3. It is differences in expectations on time investments, but not other dimensions, that we find are important. We also show that this is particularly true for those with strong beliefs on absolute advantage. A mental model of differences in time preferences is consistent with a version of beliefs on absolute advantage where beliefs originate from how women and men form preferences on free time. Differences in these preferences could then put significant pressure on women's labor market decisions, as it suggests the mental model will be a comparison between maintaining a career at the expense of time investments to children. The gain in resources from a mother working would then need to offset the expected time loss. In Section 4.2.1, we study responses to an open ended question that further confirms this mental mapping is what respondents tend to have in mind.

Fourth, we complement our survey with an information treatment about children's performance on tests when mothers work full-time and assess how beliefs and policy views respond.[2] Using a longitudinal survey from the UK, we draw a school performance measure as the pass rate of five or more GCSEs taken during adolescence. We split the pass-rate by mothers who worked either part-time or full-time while the child was in primary school, and we condition this comparison on families with similar education and income levels, informing all participants of this fact along with the average pass rate among the families with part-time working mothers. We then collect an incentivized expectation on the average pass rate for families with full-time working mothers.[3] The differences between the part-time mother and full-time mother families is small (73% *versus* 75%), suggesting that in families where mothers work full-time, children do just as well. Importantly, it is this descriptive difference that we are interested in as a stylized fact that participants may be uncertain about. Indeed, we find that there is an asymmetry in the perceptions. Participants tend to underestimate how well children of full-time mothers actually do. Next, half of the sample is randomly allocated to get the correct information, forming our treatment.

Following the treatment, we collect a set of outcomes to test whether views about how well children do when mothers work longer can be nudged by facts. Post-treatment, we draw another incentivized quantitative belief in the same way. This time, we focus on the share of children with an abnormal level of behavioral problems when mothers

[2] Our design is in the spirit of Haaland and Roth (2020) and Haaland and Roth (2023) who use incentivized beliefs as information experiments on beliefs about immigration and racial discrimination.

[3] The incentive is a cash bonus if the answer is within a small bandwidth around the actual pass rate.

work full-time. Participants also provide written responses explaining what guided their quantitative answer, which we categorize into two classifications. The first is based on whether their responses reflect harm or no harm to children from mothers working, and the second is based on the mental model their answer implies. We also draw a scale of self-reported gender norms about the role of mothers.

Participants react to the information updating beliefs, leading to Result 4 in Section 4.2.1. We find that they reduce expectations on children's problem behaviors by 5.2% and consistently move from underestimating how well children do when mothers work full-time toward more accurate beliefs, *i.e.*, closer to the truth. Also, in their written responses, they shift views away from a harmful expectation by 22%, and on self-reported norms, they show a slight move toward more liberal gender norms, by about 3% of the mean. Further, we show that belief updating in response to the information is robust to a range of concerns, including the risk of experimenter demand effects.[4] Thus, information that corrects uncertainity over how well children do when mothers maintain careers can improve misperceptions nudging beliefs toward accuracy.

Next, we look at policy support. With our focus on a small fact as the information treatment, it is hard to expect large changes in policy views, because variation is likely more limited. Indeed, in Section 4.2.2, this is what we generally find. Results are weak but go in the direction of increasing support for policies that may facilitate mothers returning to work. Further, in an obfuscated one-week follow-up, we look at additional policy support measures. While aggregate results are null, we find significant increases in support for more free childcare hours across multiple sub-groups who held stronger views on absolute advantage. Overall, the treatment weakly improves support for policies helping women with children work longer. We see this as a motivator for further work to understand how the intensity and type of information both move beliefs toward accuracy and updates political will. For instance, stories with accurate information over statistics may serve to be more salient and long-lasting in how they influence policy positions (Graeber et al., 2024).

Altogether, our paper shows that beliefs on absolute advantage are real and cover a broad spectrum of society, giving weight to their perceived role in labor market decisions post child-birth. The mental models that people have in mind tend to center around expectations about the time investments put into the child. This suggests that people hold different beliefs about the preferences that mothers and fathers hold. Information about how well children actually do when mothers work full-time shifts people toward accurate perceptions and reduces the degree of harm they expect for the child. Thus, at

[4] At the end of the main survey, we ask respondents to respond in a text box with what they thought the survey was about. We coded their answers based on whether they appeared to understand that the survey was about perceptions of mothers working and dropped these respondents in a robustness check.

least some degree of beliefs on absolute advantage centered around time preferences, can be malleable to removing uncertainty with information.

Related literature. Our work contributes to the literature on gender gaps and motherhood penalties (Blau and Kahn, 2017; Cortés and Pan, 2023; Kleven et al., 2019). Under-representation of women in the labor market has economic consequences through being costly in terms of economic efficiency (Hsieh et al., 2019). We help understand one root of mothers sorting out of the labor market through societal beliefs on absolute advantage and contribute by effectively estimating these beliefs. Additionally, we demonstrate the mechanisms people have in mind that inform these beliefs and represent targets for correcting uncertainty and misinformation.

Thus, we relate to the literature on gender norms and the role that they can play in constraining women's behavior and preferences for work (Blau and Kahn, 2017; Cortés and Pan, 2023). Recent evidence from Norway (Andresen and Nix, 2022) shows that motherhood penalties differ substantially between women in heterosexual couples and same-sex couples, suggesting that gender norms may play an important role. Perceptions of gender norms, however, can be incorrect. Progressiveness in one's country or local area is generally under-estimated (Bursztyn et al., 2023), and information about this misperception can lead to more positive views and an increase in women's labor supply (Bursztyn et al., 2020; Cortés et al., 2022). Women also are expected to generally take more socially informed decisions than men even when actual attitudes are not different (Exley et al., 2024). Moreover, Settele (2022) shows that perceptions of the gender pay gap can be inaccurate but responsive to information about the actual size of the gap. So far, beliefs about women appear substantially heterogeneous but to some degree malleable. We turn attention to understanding the form and strength of beliefs on absolute advantage in child-rearing, what characterizes them, and whether correcting expectations on simple facts about how well children do when mothers work shifts beliefs toward more accuracy and less harmful expectations.

Our study is also related to a literature examining gender differences in decisions around work and job search. Wage growth in part-time relative to full-time work is often over-estimated and can bias decisions between full-time and part-time work (Backhaus et al., 2023; Blesch et al., 2023). This can be important for gender gaps in labor markets, as women are typically observed to work fewer hours than men and are more likely to work part-time (Cortés and Pan, 2019; Goldin, 2014). Women also tend to sort into less demanding jobs in terms of working time (Wiswall and Zafar, 2017; Maestas et al., 2023), with job amenities important factors that women, more so than men, consider in the decision making about their job (Hotz et al., 2018; Wasserman, 2022). Moreover, women tend to have weaker bargaining power and less optimism about future earnings (Card et al., 2016; Cortés et al., 2023). Our study speaks to this literature, because beliefs on mothers' absolute advantage for children's development can explain why women sort into more flexible jobs requiring shorter hours and why they tend to hold weaker bargaining power. This is particularly salient given the expectations on time preferences that we estimate, where we find that women are expected to spend more time with children when free than men. This may act to pressure mothers out of work without substitutes to alleviate these expectations.

Additionally, we add to some recent work on the impact of paternity leave expansion (Farré et al., 2024) and on how fathers use time during paternity leave (González et al., 2024). These studies show that in Spain children had more developmental delays after paternity leave increased, while fathers spent less time on developmental activities and more time on leisure. Our survey experiment expands this literature, showing that indeed people expect mothers to spend more time on investments than fathers. Thus, beliefs on women's absolute advantage may partly be based on observations of fathers' time-use, putting pressure on mothers to compensate. We then show that when expectations on children's outcomes for full-time working mothers are underestimated, information on the facts can correct misconceptions toward accuracy.

We further contribute to a growing literature on parental time investments and parental beliefs about returns to parental time for children's skill development (Boneva and Rauh, 2018; Attanasio et al., 2020; Kiessling, 2021; Boneva et al., 2022). Parental time with children is increasing in many countries (Aguiar and Hurst, 2007; Borra and Sevilla, 2019), due partially to increasing returns to education and competition in the education market (Ramey and Ramey, 2009). One recent study examines beliefs about the effects of mothers' decision to work on children's skill development (Boneva et al., 2022). They find that beliefs on children's skills and family outcomes increase when mothers move from no work to part-time work – effects partially driven by increases in income – but decrease when moving into full-time work. Our paper explores a related though different mechanism, by focusing on beliefs about absolute advantage thereby intentionally removing a mechanism operating via income effects. We then show that beliefs shift in response to information and that this works through a shift in the mental model people have in mind.

The remainder of this paper establishes our conceptual framework in Section 2 and then moves through each of our four main results. In Section 3.1, we describe our sample and, through the rest of Section 3, we describe our survey design and estimation of beliefs on absolute advantage, as well as the mechanisms outlining Results 1 to 3. We then finish the paper in Section 4, assessing responses to our information treatment establishing Result 4.

2 Conceptual Framework

Our first objective is to effectively measure beliefs about women's absolute advantage in child-rearing — referred to throughout the paper as 'women's absolute advantage'. To provide structure for our analysis, we develop a simple Beckerian model of household labor division. The model provides us with an economic framework to interpret these beliefs and guides the development of a target beliefs distribution for estimation.

The model draws on Siminski and Yetsenga (2022) and assumes a household that allocates parental time between the home and the workplace. The home-time of the mother (m), the father (f), together with earnings (e), feed into their child's human capital production function as follows:

$$\text{Child human capital:} \quad HC(m, f, e) = m^{\rho_m} f^{\rho_f} e^{\rho_e}.$$

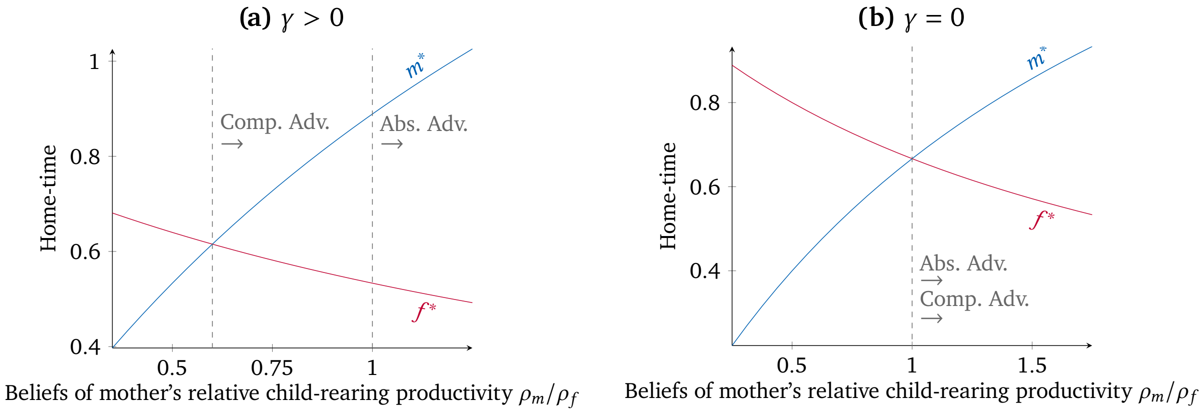
Here, ρ_m, ρ_f, and ρ_e represent the household's beliefs regarding the elasticity of maternal time, paternal time, and earnings, respectively, in producing human capital. We say that the mother has an *absolute advantage in child rearing* if $\rho_m > \rho_f$. Note that this definition incorporates both cases where the mother is more effective at child-rearing per hour spent and cases where mothers allocate more of their home-time to child-rearing activities. Indeed, in section 3.5 we use our survey design to disentangle these two sources of absolute advantage.

Each parent has an endowment of one unit of time, which can be allocated either to the home or the workplace. The father earns a wage rate of W, while the mother earns $(1-\gamma)W$. The parameter $\gamma \in [0, 1]$ reflects the earnings gap between the mother and father, for instance due to the existence or lack of family-friendly workplace policies. The household's budget constraint is given by:

$$\text{Budget constraint:} \quad e = (1-m)(1-\gamma)W + (1-f)W.$$

The key insight from the model is that household members will specialize in market work or home-production according to *comparative advantage*. This can stem either from differences in market productivity (captured by γ) or from differences in presumed child-rearing productivity (captured by ρ_m and ρ_f). In Figure 1, we highlight this in two empirically relevant cases, with the formal derivation presented in Appendix A.1. Panel (a) of Figure 1 demonstrates the case where $\gamma > 0$, hence the mother faces a wage penalty, or equivalently, fathers have an absolute advantage in market work. In this scenario the mother specializes in home-production even in the absence of gendered beliefs (*i.e.*, when $\rho_m = \rho_f$). In contrast, panel (b) shows the case where $\gamma = 0$, so that wage potentials are equalized. Here, the mother will only undertake the majority of home-production responsibility if she is believed to have an *absolute advantage in child-rearing* (*i.e.*, if

Figure 1. Optimal Child-Rearing Allocation under Different Beliefs



Note: *Comp. Adv.* and *Abs. Adv.* refers to the mother's comparative and absolute advantage in child-rearing.

$\rho_m > \rho_f$). Insofar as people hold beliefs that mothers' have an absolute advantage in child-rearing, policies aimed at closing the earnings potential gap of mothers and fathers (captured by a reduction in γ) will not be sufficient to equalize labor market outcomes. Thus, beliefs on mothers' absolute advantage are highly relevant for policy outcomes.

Our survey experiment allows us to isolate beliefs of absolute advantage from beliefs of comparative advantage, by holding earnings fixed in scenarios where we vary whether the mother works longer hours ($MWL = 1$) or the father works longer ($MWL = 0$). Using the language of the model, the beliefs that we target empirically can be written as

$$\theta_{i,e} := \widetilde{HC}_i(\underbrace{h_s, h_\ell}_{MWL=1}, e) - \widetilde{HC}_i(\underbrace{h_\ell, h_s}_{MWL=0}, e). \tag{1}$$

$\widetilde{HC}_i$ represents person i's beliefs of the human capital of a child growing up with family income e and parental home-time inputs h_ℓ, h_s representing long and short hours respectively such that $h_\ell > h_s$. Now, it is easy to show that $\theta_{i,e} < 0$ *if and only if* $\rho_m > \rho_f$. Hence, empirically testing the sign of $\theta_{i,e}$ is equivalent to testing whether the mother is believed to have an absolute advantage in child-rearing in the model, giving our empirical results a close model analogy. In the next section, we describe how our survey experiment is structured to capture these beliefs and to investigate the mechanisms driving them.

3 Hypothetical Beliefs Elicitation: Design and Results

In this section, we address five key points. First, we define our sample selection, recruitment, and demographics. Second, we present a hypothetical design through vignettes to elicit beliefs on a child's future outcomes when a mother works longer hours relative to a father. Third, we describe our estimation strategy and results to study within-person average estimates relevant to equation (1). Fourth, we describe how we empirically extract individual perceptions, by approximating an individual-level measure of equation (1), and how these vary across individuals' characteristics. Fifth, we investigate channels that can give rise to these beliefs.

3.1 Sample

We conducted our experiment on the online platform Prolific, recruiting 1,056 participants.[5] We had two main inclusion criteria, requiring participants to be (i) parents of at least one child aged 18 or below, and (ii) currently residing in England.[6] Throughout this paper, we follow our pre-registered analysis plans with some minor deviations on extended results. We point these out where relevant and describe them further in Appendix Section E.

We contrast our participants' demographics with current parents living in the United Kingdom using the latest wave (2022) of Understanding Society (US 2022). For comparison purposes, we restrict the US 2022 sample to parents of at least one child aged 18 or below and who live in England. We use only the latest wave of Understanding Society to be as close as possible to contemporaries of our respondents. In the Appendix, Table B.1, we show that our sample is similar to Understanding Society on some dimensions but over-sampled on higher education and monthly net earnings. Later, we will also show that our results are not fully driven by those with high education or income. Additionally, we will re-weight some of our key analyses in robustness checks, showing that our evidence and conclusions are unaffected. These weights are constructed with a standard "raking" procedure described in the Appendix, Section B.1. Finally, based on life histories, we show that mothers in our sample have experienced an average 29% drop in employment probability post-child birth (see Figure D.4 and Section D.1.3). This is entirely consistent with the 25-30% employment penalities observed across the US and Europe by Kleven et al. (2023), indicating that our sample looks very similar in terms of employment experiences and parenthood relative to the wider population.

3.2 Hypothetical Design

Framing. We use six hypothetical scenarios in vignettes to elicit participants' beliefs on children's human capital accumulation in response to women *versus* men working longer hours in the labor market. The following is the text participants see to set the stage for

[5]The survey design is browser-based and built using the oTree framework (Chen et al., 2016).

[6]We focus on England only, as later in the surevy we will use a metric (GCSE pass rates, see Subsection 4.1) mainly known in England. In other countries of the United Kingdom, the names, content, as well as the exam requirements of GCSEs are typically different.

the scenarios, and we further provide screenshots of the online survey in the Appendix, Subsection D.2.

> We are interested in your beliefs about children's future outcomes, comparing families with different financial resources and time demands.
>
> **Setup:** Please imagine an average family in your community. Suppose this family consists of a father and a mother who are both employed, and they have a boy (girl, *randomized*) who is aged 10 (4, *randomized*). Suppose household expenditure decisions are made jointly by the father and the mother, and this hypothetical family spends 10% (20%, *randomized*) of their total income on the child's educational and extracurricular activities such as clubs, tutoring, music, sports, etc.
>
> We will show you different scenarios, and ask your opinion about the likelihood that the child will be successful in education and the labour market. There are no clear right or wrong answers, and we know these questions are difficult. Please try to consider each scenario carefully and tell us what you believe the likely outcomes will be.

Randomization in the setup. We randomize several features in the setup. These are whether the participant reads that the family has a boy or a girl, the age of the child (4 years old *versus* 10), and the share of income (10% *versus* 20%) spent on the child's educational and extracurricular activities (denoted by SSE_i below). These randomized features enable us to assess whether participants paid attention to the vignettes, and to later assess whether beliefs differ across these features. Table B.3 in the Appendix confirms that these features are balanced across participants.

Scenarios and outcomes. Next, for each participant, we iterate through a set of scenarios (six in total) — presenting three scenarios per page — and varying two components: (i) whether the father or mother works longer hours, and (ii) the hourly wage of the parent who works longer hours. An example scenario is as follows:

> The **father** works **35** hours per week at a wage of **£12** per hour.
>
> The **mother** works **42** hours per week at a wage of **£17** per hour.

We then ask each participant their beliefs on the probability that the hypothetical child will eventually graduate from university, using a 0–100 scale with a slider. Additionally, we ask them for the child's earnings rank at age 30 relative to other 30-year-olds in terms of percentile rank using a 1–99 scale on a slider.[7] We iterate on the scenarios, and at

[7]To familiarize participants with the scaling used throughout the survey, we provide them with an "introduction to scale" (see Figure D.5 in the Appendix), common to all participants, before displaying the hypothetical scenarios.

each, re-collect these expectations/beliefs for those two dimensions. Example images of what the participants see here are presented in the Appendix, Section D, Figures D.7, and D.8.

Randomization in the scenarios. Table 1 below contains the design for iterating through scenarios. Participants work through two pages, one for a mother and one for a father working longer hours, with each containing three scenarios. Importantly, the wages they see when a mother works longer hours will be exactly the same as in scenarios with the father. To avoid order effects, we randomize whether each participant starts with the man or woman working longer hours. We also randomly draw the ordering of wages shown within each page so that participants do not move sequentially through lower to higher wage changes. In all cases, we hold constant the wage of the parent working fewer hours.

We further randomize whether the wage profile of the hypothetical parent working longer hours has a lower bound of either £12 or £17 and an upper bound of either £22 or £27. This allows across participants for the overall wage profile to range from £12 to £27. We contrast the distribution of weekly household labor income across wage profiles in our design with the distribution drawn from the 2022 wave of the Family Resources Survey. Overall, Figure D.1, in the Appendix, shows that we have good coverage over this distribution in England — although our hypothetical distribution does not cover the top 25% of the earnings distribution.

Finally, the weekly number of hours worked is randomized across participants. Half of the sample sees both parents working full-time with one of them working longer hours (42 *versus* 35 hours per week), and the other half sees a full-time working parent and a part-time working parent (36 *versus* 20 hours per week). The former is referred to as the "FT–FT" design, while the latter is referred to as the "FT–PT" design. We will use this later for heterogeneity.

Table 1. Design of Hypothetical Scenarios

	Man Works More		Woman Works More	
	w_m	w_f	w_m	w_f
$k = 1$	£17 (£12)	£17 (£12)	£17 (£12)	£17 (£12)
$k = 2$	£22 (£17)	£17 (£12)	£17 (£12)	£22 (£17)
$k = 3$	£27 (£22)	£17 (£12)	£17 (£12)	£27 (£22)

Notes: This table presents the design of our hypothetical scenarios, where w_m is the man's hourly wage, and w_f is the woman's. Participants here are randomized into either the higher or lower wage profile (in parentheses).

Attention and confidence. First, we regress each of our collected expectations (graduation likelihood and earnings rank) on the randomized features in the vignette setup and a pre-registered set of controls. Results are reported in Table 2.[8] We see strong responses on a number of design features consistent with our participants paying attention to the design details. Particularly, seeing a large share of the family budget allocated to educational activities for the child or seeing a higher wage profile strongly increases positive expectations. Second, we follow Haaland et al. (2023) to test participants' attention to the survey and confidence in their answers. Before completing the hypothetical scenarios, we provide participants with a paragraph of text, wherein we ask them to report that their favorite color is "turquoise". Below this paragraph, we ask participants "what is your favourite colour?". In our survey, 95% (1,003) of our participants passed this attention check, suggesting strong attention to our survey. Next, after the hypothetical vignettes, we ask participants to what extent they are sure about their answers. 75% of participants (795) reported being at least somewhat sure of their answers.[9] Later, we perform robustness checks (see Subsection 3.3) using these screeners, to test the reliability of our estimates.

3.3 Results: Hypothetical Beliefs Elicitation

We now test whether beliefs about children's future outcomes vary based on whether in a family the mother or the father works longer hours.

Empirical strategy on gendered beliefs. Empirically, we provide estimates for the within-person average difference in beliefs, holding constant earnings potential across a mother and a father. We approximate an average related to the individual measure we defined in equation (1) of the conceptual framework. Based on our design, this leads to the following estimation target:

$$\delta = \frac{1}{N}\frac{1}{K}\sum_{i=1}^{N}\sum_{k=1}^{K}\theta_{i,k}(MWL),$$

where we look at a within person average difference in a child's future human capital accumulation over K different levels of earnings potential. In the survey, our collected expectations on a child's future outcomes ($y^{o}_{i,j,k} = [y_{i,j,k}{}^{\text{graduation}}, y_{i,j,k}{}^{\text{rank}}]$) vary across individuals and the wage levels (k). These wage levels change in exactly the same way for scenarios with a mother working longer hours ($MWL_{j=1}$) versus a father ($MWL_{j=0}$).

[8]Where participants' characteristics are controlled for in this study, we use the following pre-registered set: participant's gender, a quadratic in age, an indicator for whether they have at least a university degree, employment status (full-time *versus* part-time or less), and ethnicity (white *versus* non-white).

[9]We provide screenshots of the attention check and confidence questions that participants actually see in the Appendix, Section D (see Figures D.6 and D.13).

Table 2. Design Effects Across Participants

	(1) $\mathbb{P}$(graduate)	(2) Earnings Rank
Child is a girl	1.019	1.858*
	(1.06)	(1.00)
Child is aged 4	-0.107	0.451
	(1.07)	(1.02)
SSE_i: 20%	2.807***	1.370
	(1.06)	(1.01)
FT–FT profile	2.107**	2.077**
	(1.06)	(1.01)
High wage profile	7.658***	5.280***
	(1.07)	(1.00)
Mother shown first	0.050	0.569
	(1.06)	(1.00)
Participants	1056	1056
Observations	6336	6336
Individual Controls	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are in parentheses and clustered on individuals. The probability to graduate ($\mathbb{P}$(graduate)) is scaled between 0 and 100. Earnings Rank is the percentile ranking expected for the child at age 30 among other 30 year-old. SSE_i is an indicator for seeing the share of budget spent on educational expenditures at 20% instead of the 10% in the vignette setup. The FT–FT design presents both parents as full-time with one working longer hours (42 *vs*. 35). The "mother shown first" variable is equal to 1 when scenarios with $MWL = 1$ (mother works longer hours) were shown first or 0 when scenarios with $MWL = 0$ (father works longer hours) were shown first. Individual controls include the pre-registered set of participants' characteristics.

We aggregate the within-person difference in these measured beliefs over MWL_j. If there are no gendered beliefs, then the average change in beliefs will be the same ($\hat{\delta} = 0$), regardless of who works the longer hours. While an estimate of $\hat{\delta} < 0$ will be consistent with beliefs that women hold an absolute advantage. In this case, average expectations are that it is more harmful for children's human capital accumulation if women work longer hours compared to men. Following our pre-registration the main specification is:

$$y^o_{i,j,k} = \alpha_0 + \delta MWL_j + \tau_k + \mu_i + \epsilon_{i,j,k}. \quad (2)$$

Participant fixed effects are captured by the vector μ_i and vignette household income fixed effects by τ_k. In some specifications, we replace μ_i with the pre-registered set of participant's characteristics, which are the following: gender, a quadratic in age, an indicator for whether they have at least a university degree, employment status (full-time *versus* part-time or less), and ethnicity (white *versus* non-white).[10]

Average estimates of gendered beliefs. Results for each outcome (graduation likelihood, earnings rank) based on equation (2) are presented in Table 3.

Table 3. Beliefs About Mothers Working Longer

	(1) $\mathbb{P}$(graduate)	(2) $\mathbb{P}$(graduate)	(3) Earnings Rank	(4) Earnings Rank
$MWL_{j=1}$	-0.933***	-0.933***	-0.668**	-0.668**
	(0.299)	(0.299)	(0.268)	(0.268)
Mean Dep. Var	56%	56%	49^{th}	49^{th}
Participants	1056	1056	1056	1056
Observations	6336	6336	6336	6336
Indiviual Controls	Yes	No	Yes	No
Individual Fixed Effects	No	Yes	No	Yes
Scenario Income Fixed Effects	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Standard errors are clustered on individuals. Expectations on the child's probability to graduate ($\mathbb{P}$(graduate)) range between 0 and 100 with a mean of 56 representing a 56% expected likelihood. The expected percentile earnings rank when the child is 30 years old lies between 1 and 99. Individual controls include the pre-registered set of participants' characteristics.

Result 1. *Beliefs on children's future outcomes are on average worse when a mother works longer hours compared to when a father works longer hours for the same wage.*

Our estimates of $\hat{\delta}$ return significant and negative effects for scenarios with the mother working longer hours. In these scenarios, participants reduced their expected probability that the child will graduate university by nearly 1% and earnings rank at age 30 by about 0.67^{th} of a percentile. While these magnitudes are not large, they suggest that even when earnings potential is equalized between mothers and fathers, hesitancy over the mother working longer hours may remain. This is consistent with beliefs that mothers can hold an absolute advantage in child rearing, and it forms our main result of Section 3. In the remainder of this section, we unpack this further and add more context before moving to assess an information treatment.

Heterogeneity by participants' characteristics and past experiences. Appendix Tables B.4 and B.5 present OLS results for equation (2) stratified by participants' characteristics, their past experiences of their own-mother working, and the extent of their own-motherhood penalty (for women). Across characteristics, in Table B.4, we find a generally homogeneous pattern with some differences in the point estimates. The negative

[10]Note that 6 respondents listed "other" or "prefer not to say" for gender. We set these to 0 and control for an indicator flagging them.

effects in MWL scenarios are somewhat stronger among men, those born outside the UK, university degree holders, part-time or less employed participants, and those who voted conservative, other, or none, at the last UK General Election. While the university result appears surprising, less surprisingly, beliefs on absolute advantage appear to be strongest within more conservative groups. More interestingly, in Table B.5, we see suggestive evidence of role model influence. The effects are much weaker or non-existent for those whose own-mother worked full-time when they were young (< 12). Additionally, among women, the MWL effects are strongest for those who experienced a higher than median motherhood penalty in full-time employment post birth.[11] The effect disappears among those with a lower motherhood penalty, suggesting that norms are strongly associated with post-birth labor market sorting. We return to these points in the next section when we investigate beliefs at the individual-level.

Heterogeneity by hypothetical design features. We report heterogeneous effects for the MWL effects stratified by the randomized hypothetical design features in the Appendix, Table B.6. First, we observe stronger negative effects in scenarios with a boy (as opposed to scenarios with girls). The results, based on the gender of the vignette child, point toward different expectations on the needs of children and the role of mothers. While beyond the scope of this paper, this finding aligns with evidence that boys, especially in disadvantaged families, are more responsive to parental inputs (Bertrand and Pan, 2013; Autor et al., 2019; Lei and Lundberg, 2020). If boys are viewed as less resilient than girls and maternal time is perceived as 'higher-quality' time, then we should indeed expect stronger beliefs that their development and educational outcomes may suffer more from reduced parental input quality when mothers work longer.

Second, the effects are driven by scenarios with, on average, lower hypothetical household incomes and scenarios with a lower allocation of resources (10% instead of 20%) to the child's educational activities. Together, these results suggest that people believe mothers are more important than fathers for the production of a child's skills until income is high enough or enough resources are devoted to the child. One implication is that this places pressure on mothers who have less disposable resources when deciding whether to continue careers, suggesting support for mothers to work requires help to close resource gaps and alleviate the pressure these beliefs may create. In relation to our conceptual framework, these results imply people may view time and money as substitutable inputs in the development of child human capital — an assumption not embedded in our baseline model. However, as shown in Appendix A.2, introducing two modifications to the child human capital production function realigns the model with the data. Specifically, we find that a model where time and monetary inputs are gross

[11] We construct the motherhood employment penalty from the life histories we ask participants at the end of the survey. The computation of this penalty is described in Subsection D.1.3, in the Appendix.

substitutes, and exhibit decreasing returns to scale, successfully replicates the observed pattern: the effect of mothers working longer decreases as household earnings increase.

Third, and finally, we see that the effects are more substantial when participants saw the father working longer hours on the first page (and thus mothers on the second page). Because we randomize the order, meaning the page order is orthogonal to the MWL indicator, then an order effect whereby people simply change beliefs based on the page number will not bias our $\hat{\delta}$-estimate in equation 2. For instance, if participants always downgrade their expectations on the second-page, then when mothers are shown first as working longer hours, expectations with fathers on the second-page will be pushed up by any beliefs on absolute advantage but pushed down by this order effect hiding the true degree of beliefs on absolute advantage. While for those randomized to first see fathers working longer hours, then on the second-page with mothers, both beliefs on absolute advantage and the order effect can widen the differences in expectations. Importantly, because we randomize the order, the net effect over all participants removes any order effect leaving the beliefs we are after.[12] Alternatively, this heterogeneity may arise because the gender difference in the two hypotheticals becomes more salient when participants encounter first the normative family arrangement with the father working longer hours priming attention to their core beliefs.

Robustness checks. Finally, we test the robustness of our key finding (Result 1) by implementing different sample restrictions and checks, and report these in the Appendix, Table B.7. First, we exclude those who reported being unsure or very unsure about their answers to the vignette scenarios. Second, we exclude participants who did not pass the attention check. Third, as an additional check against inattention, we exclude participants with the 5% lowest and highest response times. Fourth and last, we re-weight our sample to match the national population distribution (see Subsection B.1). Our main result is robust to all of these checks, with the coefficients on MWL_j in Table B.7 about the same magnitude as the ones we find in Table 3.

3.4 Individual Perceptions

We want now to aggregate elicited beliefs at the individual-level, in order to approximate equation (1) from the conceptual framework. These are individual average perceptions. In our design, this equates to the following formulation:

$$\theta_i = \frac{1}{K}\sum_{k=1}^{K} \theta_{i,k}(MWL),$$

[12]Indeed, when we include a scenario order as a control variable in our regression, estimates remain unchanged.

where we have collapsed the difference in beliefs around MWL_j to the individual-level.

Approach and consistency of measures. To aggregate at the individual-level, we estimate equation (2) for each person in the sample, and each expectation outcome o, further dropping the household income fixed effects and individual fixed effects. The individual specific estimates of MWL_j recover each respondent's average gap between scenarios with mothers *versus* fathers working longer hours. For each expectation outcome o, we label the individual perceptions to mothers working longer hours compared to fathers as $\theta_i^{\text{graduate}}$ for the probability of the child to graduate from university and θ_i^{rank} for the earnings rank at age 30. For each of these θ_i^o measures, the scale is increasing in more positive views about children's future outcomes when women work longer hours relative to men, with 0 implying no expected difference. The distribution for these is displayed in the Appendix, Figure B.1, and in the Appendix, Figure B.2, we show that these two measures are consistent with one another.

Associations with participants' characteristics. Both θ_i^o measures vary across respondents. We document this heterogeneity in Table 4 regressing each θ_i^o on a set of characteristics. Stronger beliefs of absolute advantage for mothers relative to fathers are predicted by respondents who are older, male, have more children, have a university degree, and conservative voters. More positive perceptions are characterized by those who have higher incomes or partners with higher incomes and particularly by those whose mother worked full-time when they were growing up (< 12).[13] Next, the role model effects appear to be strong from exposure to a mother who worked full-time while the respondent was a child. Moreover, exposure to a full-time working mother while an adolescent does not appear to matter or if anything works in the opposite direction. Thus, the formative years of early childhood are linked with later beliefs and exposure to a working mother shapes later perceptions. Our results align with the literature on the role model effects through intergenerational transmission of gendered beliefs particularly through the mother (Fernández and Fogli, 2009; Alesina et al., 2013), and underscore how the formation of these beliefs evolves with age (Bénabou and Tirole, 2002). In addition, women who have a higher post-birth employment penalty than the sample median hold more negative views on mothers working longer hours. This is qualitatively consistent with recent evidence showing that traditional mothers in the UK experience a higher motherhood penalty in earnings and labor supply (Boinet et al., 2024).

[13]While it is perhaps surprising that university graduates associate with stronger views on absolute advantage, this is conditional on age, employment, income, gender, political party voted for and more which all have intuitive signs.

Table 4. Associations of Beliefs with Participants' Characteristics

	All Participants		Women	
	(1) θ^{graduate}	(2) θ^{rank}	(1) θ^{graduate}	(2) θ^{rank}
FT working mother when age < 12	1.263***	2.683***	2.244***	5.022***
	(0.399)	(0.336)	(0.671)	(0.566)
FT working mother when age ≥ 12	-0.360	-0.435	0.902	-2.086***
	(0.351)	(0.307)	(0.570)	(0.516)
High motherhood penalty			-2.300***	-0.726*
			(0.476)	(0.399)
Woman	-0.205	0.891***		
	(0.353)	(0.306)		
Age	-0.253*	-0.708***	-0.190	-0.933***
	(0.143)	(0.147)	(0.275)	(0.241)
Age^2	0.003	0.009***	0.003	0.013***
	(0.002)	(0.002)	(0.003)	(0.003)
White	1.361***	0.593	-1.082	2.365***
	(0.431)	(0.415)	(0.704)	(0.643)
Born in the UK	1.290***	1.248***	1.176	1.598**
	(0.488)	(0.429)	(0.724)	(0.645)
University graduate	-1.041***	-0.706***	-2.007***	-0.727
	(0.320)	(0.274)	(0.526)	(0.460)
FT employment	-0.166	0.522	0.141	0.614
	(0.388)	(0.330)	(0.507)	(0.438)
ln(Household income)	1.824***	1.709***	2.285**	3.015***
	(0.575)	(0.474)	(1.122)	(0.844)
Number of children	-0.853***	-0.628***	-0.132	0.469*
	(0.181)	(0.195)	(0.261)	(0.251)
Vote: conservative (*ref*. liberal)	-0.744*	-0.967***	0.475	-1.196**
	(0.400)	(0.353)	(0.698)	(0.567)
Vote: other or none (*ref*. liberal)	-0.336	-1.004***	0.825	-0.342
	(0.363)	(0.357)	(0.568)	(0.630)
Participants	1040	1040	525	525

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. This table presents OLS results for our individual perceived returns over (1) the likelihood for the hypothetical child to graduate from university, and (2) the earnings rank of the hypothetical child among his 30-year-old peers, on a set of participants' characteristics and past experiences. The inclusion of the high motherhood penalty dummy — defined as having a higher post-birth employment penalty than the median — is for women only. For the own-mother's employment during the participant's childhood and adolescence, we drop observations that were listed as not applicable (N = 16). We also collected this information for their father's but 93% had a full-time working father when they were less than 12, and 90% when they were adolescents. Thus, we do not report results due to small cell sizes for the part-time or less category. Six respondents listed "other" or "prefer not to say" for gender. We code these as 0 but control for an indicator flagging them. Voting is grouped over three categories in the last UK general election. These are Conservative or Reform UK; Labour, Liberal Democrats, or Green Party; and other or none.

Associations with participants' choices. We also look at the association between these individual beliefs and participants' time spent helping their child develop their skills, doing outdoors activities, and working in the labor market.[14] Results are presented in the Appendix, Table B.8, where we regress these choices on the belief measures (θ's) including our standard control set. More positive perceptions of women working have heterogeneous predictions across women and men. These associations are not causal, possibly influenced by selection, but point toward interesting patterns. More positive perceptions among women predict less time spent on helping their children develop their skills, while positive perceptions of women working do predict more time for men. Further, perceptions are not associated with women's time in the labor market but have a positive relationship for men, suggesting that when men hold more positive perceptions (weaker views on absolute advantage for women), they spend more time in both domestic and labor market activities.

Summary. Altogether, the measures of individual-level beliefs suggest that perceptions of mothers absolute advantage in child rearing vary substantially. They are stronger for conservative voters, and are predicted strongly by the role model effect of exposure while young to one's own-mother working full-time. Additionally, beliefs on absolute advantage predict domestic time investments with children and working time, particularly among men. Later, we will use the estimated individual beliefs to evaluate how they influence responses to an information treatment. Next, we turn to elicit views on channels that may explain these beliefs on absolute advantage.

Result 2. *There is significant across-person heterogeneity in beliefs about women's advantage in a child's human capital accumulation, and the role model effects of exposure to a full-time working mother when young affect these beliefs when grown.*

3.5 Mechanisms for Variation in Beliefs

Now, we consider what channels may give rise to variation in the beliefs distribution we outlined in equation (1). We propose three main possibilities. First, people may hold beliefs about *differences in preferences*. This would imply that people believe mothers and fathers hold different valuations for time spent outside of work, whereby they expect women value spending more of their free time investing in a child's skills than do men. This channel could generate $\theta_{i,e} < 0$. Second, people may hold beliefs about the *productivity* of time investments. In this case, they may presume mothers have an absolute advantage because they believe mothers are more productive in producing a child's skills than a father for the same amount of time spent. This again would generate $\theta_{i,e} < 0$.

[14] Because we collect these at the end of the survey, for this analysis we use only the control group from the information treatment that is to come.

Third, people may believe that for a given budget, the parent who works longer, or earns more, makes the *resource allocation* decisions for monetary investments to a child. A presumption that mothers will allocate more of the budget to these monetary investments would push in the opposite direction of the other two channels.[15]

Here, we investigate each of these as a way to better understand the beliefs we document in Result 1. Additionally, we look at whether people hold different expectations on the likelihood of holding a university degree for mothers and fathers, based on who works longer hours. For the analyses in this section, we introduced new vignettes to participants, but rather than using a within-person design, the focus is on randomized features across participants that target each of these channels. We provide a description of the approach here and the survey details in the Appendix, Subsection D.2 — in particular, see pages 5 to 8.

Expectations on time preferences: design. Beliefs on differences in preferences imply people will expect a mother to spend more time on activities with their child than a father given the same free time. To investigate this, we present respondents with a child aged 11 who will soon take the Key Stage 2 national test.[16] We randomize across participants whether both (*versus* neither) hypothetical parents have a university education and, importantly, whether the father (mother) has a busy week ahead with only the mother (father) free to help. We then ask how much time they expect will be spent helping the child study for the test and how much time they expect will be spent on extracurricular activities.[17] All participants are informed of the average time (30 minutes) spent per week on teaching activities by parents in the 2013 British Time Use Survey to give them a common contextual reference.[18]

Expectations on time preferences: results. We regress the expectations for time spent studying and extracurricular activities on an indicator for seeing the scenario with the mother free instead of the father, an indicator for seeing the scenario with university educated parents, while controlling for participants' characteristics. These are reported in column (1) of Table 5 and in column (2) we add an interaction between these two randomized features. Respondents expect mothers to dedicate more time than fathers, particularly for study help (about 13 minutes more) and in scenarios where the presented

[15]Evidence from the literature generally rejects the income pooling hypothesis, indicating that when mothers are in charge of resources (as opposed to fathers), expenditures on children tend to increase (Hoddinott and Haddad, 1995; Lundberg et al., 1997; Bobonis, 2009).

[16]A key stage refers to a level within the education systems of England, whereby a certain level of educational knowledge is expected from students. Key Stage 2 concerns pupils aged 7 to 11 who take SATs, and is particularly well known by English parents. See the UK Government website for more information.

[17]Both are answered by moving a slider in 10-minutes increments that can range from 0 to 10 hours.

[18]Currently, this is the last edition of this survey, and the sample is restricted to parents who have at least one child in the 10 to 14 age range. We further inform participants of this.

Table 5. Expectations on Time

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Participants		By $\theta^{graduate}$				By θ^{rank}			
			< 0		≥ 0		< 0		≥ 0	
Panel A: Time spent on test help										
Mother (*father*) free to help	12.945*	6.299	18.613*	-1.655	8.145	14.320	12.118	-1.481	14.122	13.988
	(6.816)	(9.467)	(9.977)	(13.710)	(9.640)	(13.508)	(9.928)	(13.870)	(9.439)	(13.330)
Both parents (*neither*) have a university education	37.728***	30.843***	36.010***	13.828	38.986***	45.020***	36.837***	22.807	37.528***	37.390***
	(6.890)	(9.957)	(10.195)	(14.098)	(9.559)	(14.085)	(10.117)	(14.397)	(9.579)	(13.987)
Both parents have a uni education × Mother free to help		13.603		45.886**		-11.659		27.521		0.276
		(13.615)		(19.796)		(18.840)		(19.856)		(19.086)
Mean Dep. Var	149.242	149.242	147.769	147.769	150.533	150.533	149.182	149.182	149.292	149.292
Panel B: Time spent on extracurricular	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Mother (*father*) free to help	2.962	-8.204	4.780	-14.253	0.646	-2.655	11.343	6.913	-4.744	-20.465
	(6.760)	(9.303)	(9.995)	(13.315)	(9.449)	(13.131)	(9.362)	(12.073)	(9.632)	(13.676)
Both parents (*neither*) have a university education	38.096***	26.528***	38.207***	17.376	36.936***	33.709**	48.499***	43.928***	30.507***	14.204
	(6.857)	(9.755)	(10.242)	(13.981)	(9.423)	(13.616)	(9.810)	(13.031)	(9.631)	(14.125)
Both parents have a uni education × Mother free to help		22.855*		43.091**		6.234		8.967		32.408*
		(13.601)		(20.065)		(18.651)		(18.892)		(19.364)
Mean Dep. Var	161.061	161.061	156.227	156.227	165.293	165.293	156.541	156.541	164.784	164.784
Participants	1056	1056	493	493	563	563	477	477	579	579
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: p <0.10; ** p <0.05, *** p <0.01. OLS results for the expectations on time spent on test help (panel A) in minutes per week, and time spent on extracurricular activities (panel B) in minutes per week, with the hypothetical child. Italicized words in parenthesis correspond to the reference category. All specifications include controls for the pre-registered set of participants' characteristics. Robust standard errors in parentheses.

parents are university educated. While in column (2), results are not significant, we find that the marginal effect of a mother having free time in the university educated scenarios is significant and about 20 minutes longer in study time than fathers (6.3 + 13.6).[19] Finally, looking beyond our pre-registered plans in columns (3) to (10), these results appear stronger for those with more negative views about women working longer hours as captured by our θ_i^o measures. We view this last step as exploratory, as it is beyond our pre-defined plans, but suggestive that those holding strong views on absolute advantage do have in mind different time preferences between mothers and fathers. Altogether, these results are consistent with beliefs on time preferences where mothers are expected to spend more time on educational activities than fathers.

Expectations on productivity: design. Now, we aim to explore beliefs on differences in the productivity of a given time investment over mothers relative to fathers. After answering the expected time questions, participants move to the next survey page where we continue the setup of the previous question. Now, however, we fix the time the parent who is free spends helping the child prepare for the test. For instance, if a participant was randomized to see that the "mother" was free on the previous question, this continues here and we pin down the time spent. We also randomize this between 30 minutes (shorter time) or 1 hour 30 minutes (longer time). Participants are asked how well they

[19]We have not reported these calculations but can make them available on request.

think the child will do compared to other students in terms of percentile rank on the Key Stage 2 test. To answer, they drag a slider ranging from the 1st to the 99th percentile.

Table 6. Expectations on Performance

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	All Participants		By $\theta^{graduate}$				By θ^{rank}			
			< 0		≥ 0		< 0		≥ 0	
Panel C: Expected rank at test										
Mother (*father*) free to help	0.002	-0.017	-0.010	-0.036	0.014	0.001	-0.019	-0.055*	0.019	0.011
	(0.012)	(0.020)	(0.018)	(0.029)	(0.016)	(0.028)	(0.018)	(0.030)	(0.016)	(0.028)
1h30 (*30 minutes*) of help	0.101***	0.084***	0.086***	0.057**	0.117***	0.111***	0.096***	0.054**	0.103***	0.104***
	(0.012)	(0.017)	(0.018)	(0.024)	(0.016)	(0.022)	(0.018)	(0.025)	(0.016)	(0.022)
Both parents (*neither*) have a university education	0.072***	0.071***	0.058***	0.064***	0.085***	0.079***	0.075***	0.084***	0.072***	0.063***
	(0.012)	(0.017)	(0.018)	(0.025)	(0.016)	(0.022)	(0.018)	(0.025)	(0.016)	(0.022)
Mother free to help × 1h30 of help		0.035		0.060*		0.012		0.082**		-0.001
		(0.024)		(0.035)		(0.032)		(0.035)		(0.032)
Mother free to help × Both parents have a uni education		0.003		-0.013		0.012		-0.012		0.018
		(0.024)		(0.036)		(0.032)		(0.035)		(0.032)
Mean Dep. Var	42nd	42nd	42nd	42nd	42nd	42nd	41st	41st	43rd	43rd
Participants	1056	1056	493	493	563	563	477	477	579	579
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: p <0.10; ** p <0.05, *** p <0.01. OLS results for the expectations on the child's test performance (rank among his peers). Italicized words in parenthesis correspond to the reference category. All specifications include controls for the pre-registered set of participants' characteristics. Robust standard errors in parentheses.

Expectations on productivity: results. We regress participants' expected percentile rank for the child at the Key Stage 2 national test on the three randomized features and participants' characteristics. The features include an indicator for the mother being free instead of the father, an indicator for the scenario where both parents have a university education, and an indicator for seeing the time spent on studying help as 1.5 hours (longer time) instead of 0.5 hour. These are reported in column (1) of Table 6, and in column (2), we add an interaction between the mother being free and two additional randomized features.[20] Remember that the amount of the time investment is pinned down in the scenario here, thus the comparison is between a mother being free versus a father for a given time investment. Overall, we do not see strong evidence for disparate beliefs on the productivity of time investments when mothers are free relative fathers. Where they do appear, it is among those with more negative views (by the θ_i^o measures) and only when the longer time investment is given. Even here, respondents only expect the child to do around 0.06 – 0.08 percentile-points better when the mother is free to help.

Expectations on resource allocation. Another possibility is that people expect more resources to be allocated to a child's educational activities when the mother earns a larger

[20] For transparency, we did not mention these interactions in the pre-registration plan directly, although we had noted we would analyze results by design features this was directly about the previous section. Thus, we put these forward with caution along with the splits by the θ_i^o measures.

share of the household budget. If so, we think this would work in the opposite direction of beliefs about absolute advantage potentially offsetting them when a mother works longer hours. Yet, we find no evidence for this in column (1) of Table 7. We randomize participants to see a mother (father) earning a larger share of the family budget and ask them for the expected share of the family budget spent on the child's educational and extracurricular activities.[21] Regressing this expectation on an indicator for those who see the mother earns more, and controlling for respondents' characteristics, returns a tight null. Additionally, we show in the Appendix, Table B.10, that the results are also null when we further split by negative and positive values of θ_i^o.[22] Thus, differences in resource allocation do not appear to drive beliefs.

Table 7. Expectations on Resource Allocation and Parental Education

	(1) Resource Allocation	(2) $\mathbb{P}$(University Graduate)		
		Mother	Father	Difference
Mother (*father*) earns more	0.007			
	(0.009)			
Works full-time (*part-time*)		0.114***	0.082***	0.032
		(0.013)	(0.013)	(0.023)
Participants	1056	1056	1056	1056
Individual Controls	Yes	Yes	Yes	Yes

Notes: p <0.10; ** p <0.05, *** p <0.01. OLS results for the expectations on (1) resource allocation, and (2) parental education. Italicized words in parenthesis correspond to the reference category. All specifications include controls for the pre-registered set of participants' characteristics. Robust standard errors in parentheses.

Expectations on parental education. Finally, people may expect part-time working fathers to be much less skilled than part-time working mothers. If so, this could explain expectations on children's future outcomes when a mother relative to a father works full-time. To explore this, we present a mother (father) working 36 hours per week for £27 per hour, while the father (mother) works 20 hours per week for £17 per hour. We then ask respondents the likelihood for each parent to hold a university degree and regress these answers on an indicator for having seen that parent working full-time in the scenario, including respondents' characteristics. The results show that there is a part-time to full-time expected education gradient. Respondents expect that a university

[21]Participants read a scenario again with a child aged 11 that reports the father (mother) earnings a net monthly income of £1,500 and the mother (father) earns £2,500, randomizing which parent earns more. Participants are then asked what share of income they expect to be spent on the child's educational and extracurricular activities.

[22]This analysis was not pre-registered. See Section E in the Appendix for more details.

degree is more likely for either the mother or father when they work full-time relative to part-time (columns 2 and 3 of Table 7). However, the difference in this expectation across mothers and fathers is negligible and not significant. Results further split by negative and positive values of θ_i^o (Appendix, Table B.10) also remain negligible.[23] Thus, we see no evidence that differences in skill expectations drive beliefs when comparing mothers working longer hours relative to fathers.

Summary. We only find weak evidence that respondents expect differences in productivity across mothers and fathers nor do they expect differences in resource allocation or skills when the mother relative to the father earns more or works longer hours. On the other hand, beliefs on preferences come through and are suggestive that people expect mothers to invest more time into a child's skills than fathers with similar free time. This would be consistent with a version of absolute advantage, where different beliefs originate from how parents form preferences in allocating their free time. In this case, mothers are believed to hold an absolute advantage because people expect them to allocate more of their time at home to productive inputs for children's human capital.

Result 3. *Respondents expect mothers to spend more time on investments to a child's skills relative to a father with the same free time, especially when a parent has higher education.*

Together our evidence in Section 3 can be summarized through three results. First, we find strong evidence of beliefs on absolute advantage (Result 1), suggesting that even with earnings potentials equalized gender gaps may remain. Second, beliefs are heterogeneous over participants' backgrounds, with role model effects during childhood important for shaping later beliefs (Result 2) and women's lower attachment to the labor market post-birth an important predictor of beliefs. Third, a mental model of differences in preferences across mothers and fathers for time investments into children appears an important element of comparisons informing participants' beliefs (Result 3).

4 Information Experiment: Design and Results

So far, our evidence is consistent with beliefs that children have worse outcomes when a mother relative to a father works longer hours. We turn now to investigate belief updating in response to information about children's educational outcomes when mothers work full-time. Our focus is on the provision of a fact and how people react to it in terms of their beliefs about how well children can do when mothers maintain careers and their views on the role of mothers. We further probe the effect of information on support for policy promoting mothers' labor market opportunities. Our sample of participants remains the

[23]Transparency: we pre-registered this design but only realized after the survey collection the best way to use the information to address the question at hand.

same as defined in Section 3.1, and throughout this section, we assess whether responses to information vary by the individual-level beliefs measures (θ_i^o) we have elicited to test whether information responses are symmetric or asymmetric over prior beliefs. Our design uses incentivized beliefs in a similar structure as Haaland and Roth (2023) who study beliefs about racial discrimination and Haaland and Roth (2020) who study beliefs about immigration and the labor market.

4.1 Treatment Design and Outcomes

To form an information treatment, we use the Millennium Cohort Study (MCS) and draw some statistics on child development and achievement. The MCS is a longitudinal study following a nationally representative sample of children born in the year 2000, and their families. We calculate the share of children passing five or more of their secondary school GCSEs with a grade C/4 or higher. This pass rate is a common metric in school league tables in England, which will likely be familiar to our sample of parents.[24] We split this metric by families where the mother worked, on average at least full-time hours per week when the child was aged 5 and 7 *versus* families where the mother worked part-time or less.[25] We draw our calculations from dual-parent homes in England and compare families whose parents have similar income and education levels. We provide more details on the data and our calculations in the Appendix, Subsection D.1.2.

Prior beliefs on GCSE pass rates. We first inform participants of this GCSE pass rate for families where the mothers worked part-time or not at all. We then collect an incentivized belief about this pass rate for families where the mother works at least full-time hours. Below is the text participants read.

> We, as researchers at the University of Strathclyde, have calculated the share of children passing five or more GCSEs with a grade of C/4 or higher.
>
> Among families where the mother worked part-time or not at all, around **73**% of children passed five or more GCSEs with a C/4 or higher. This information is also shown visually in the graph below.
>
> We then computed this statistic for families with similar income and education levels but where the mother worked full-time (35 hours or more). In these families, what percentage of children do you believe eventually passed five or more GCSEs with a C/4 or higher?

[24] See the UK Government website for further information about GCSEs results in 2023. Also see the GCSEs' subject content, by field.

[25] We use data from the age 5 and 7 sweeps, corresponding to the years 2006 and 2008, to capture the mother's working hours during the child's primary school years.

> You will gain £1.50 if your answer is within 2 percentage points of the true number.

We also present this information and question visually in a graph (see the Appendix, Figure D.14). Participants then respond by dragging a slider between 0 and 100% in increments of 1 percentage point.

We capture priors on this GCSE pass rate before giving half the sample the true information. One reason to collect this prior is that it allows another measure of beliefs but one that is not strict to the beliefs on absolute advantage equalizing earnings potential that we have in the θ_i^o measures. It can capture uncertainty, misinformation, or other dimensions unrelated to absolute advantage and allows us to look at whether receiving factual information leads to responses across multiple dimensions of prior beliefs.

Information treatment. Among families with similar education and incomes, children with full-time working mothers do just as well, if not slightly better, than those with part-time or less working mothers. This forms the fact we use as a treatment. We randomize participants to either receive the actual pass rate when mothers work longer hours – the fact – or to the control group with no information. Those assigned to the treatment are shown the statistic in text and graphically. The text is below and the visual aid is reported in the Appendix, Figure D.15.

> For mother worked full-time (35 hours or more), adjusted to have similar education and income levels as mothers working fewer than 35 hours, we found that around **75**% of their children eventually passed five or more GCSEs with a C/4 or higher.
>
> This means these children did about **2 percentage points better** compared to those of mothers working less than 35 hours per week.

Outcomes. We follow the information treatment by collecting a set of outcomes. Details about the wording and descriptive statistics are provided in the Appendix, Subsection D.2. Our primary interest is on whether people respond to information updating how they think about the effects of a mother working full-time. We look at these views in three ways.

First, we collect another incentivized belief, focusing this time on externalizing behavioral problems when mothers work part-time or less compared to full-time or more across families with similar education and income.[26] Relative to our question on GCSE pass rates, we use a different response scale and change its direction to mitigate concerns over numerical anchoring (per suggestions in Haaland et al., 2023). Below is the text shown to participants to elicit this behavioral belief.

[26] The share of children at high risk of behavioral problems when the mother works full-time is 16.573%.

> The data that we used to calculate the share of children passing five or more GCSEs also provides information on the children's externalizing behavioral problems at age 7 (*e.g.*, conduct problems and hyperactivity/inattention).
>
> Among families where the mother worked part-time or not at all, **out of 100 children** aged 7, we found that around **17** had an abnormal level of behavioural problems.
>
> We then computed this statistic for families with similar income and education levels but where the mother worked full-time (35 hours or more). In this group, **out of 100 children**, how many do you believe had an abnormal level of behavioural problems?
>
> You will gain £1.50 if your answer is within 2 points of the true number.

Participants are asked to report their expectation in a text box.

Second, we ask them to write in complete sentences what guided their answer to this question (see Appendix, Figure D.18). We use this to gain insight on what participants are really thinking about when responding to the quantitative question on abnormal problem behaviors. We coded their responses as suggesting it is harmful for the child when the mother works full-time, not harmful, or an unclear answer (13% classed unclear).[27] Further, we build another classification with more detail to flag whether respondents expect lower time investments from mothers working full-time or another mechanism. We focus on the harmful/not harmful categorization but look at the extended classification for more context. As discussed in the Appendix, Section E, our classification scheme departs from our pre-registered classification plan as we realized afterwards the best way to code these responses to test our objectives.

Third, we ask five questions related to gender norms on the role of mothers in the family. Participants are asked to indicate their level of agreement on a 1-5 scale with each statement. The questions participants see are presented in the Appendix, Table D.19, and are drawn from the British Household Panel Survey, as these are commonly used in the literature (*e.g.*, Flèche et al. 2020). We sum answers to these into a scale where higher values reflect more liberal views.

Finally, we collect government policy views about subsidized childcare and paternity leave policies, whereby participants indicate their level of agreement. Details are in the Appendix, Figure D.17. We then code these into binary outcomes for high support split by the median.

[27]We read and manually coded each response. We experimented with textual analysis on a training set, but participants use a wide range of language in their responses leading standard machine learning tools to classify poorly (accuracy of 60%). Participants, however, provided often rich answers, and we could clearly classify nearly all responses outside of a small percentage (13%).

Obfuscated follow-up. We invited participants back one week later and continued our look at self-reported policy views. Participants received a generic invitation from Prolific to take a five-minute survey, which did not reveal the connection to the main survey.[28] Among the 1056 participants of the first survey, 86% (893 respondents) took part in the obfuscated follow-up. Further, we asked four questions but only two of these relate to our research questions and are about policies to lower the cost for mothers to work, *e.g.*, on childcare policies. The additional questions serve to obscure a link between this survey and the original. These questions, as well as answer modalities, are presented in the Appendix, Subsection D.2.2.

Heterogeneity in beliefs about children's skills. Before we proceed to estimate the effect of information, we look at how our measures of beliefs vary with the posterior beliefs (expectations on behaviors) and gender norms. We demonstrate, in the Appendix, Figure C.1, that the cumulative distributions of GCSE pass rates and the posterior expectations have a high degree of variation for estimating our information treatment effect. Next, using the control group only and conditional on participant characteristics, we show that all of our beliefs measures ($GCSE_i$, ${\theta_i}^{\text{graduate}}$, ${\theta_i}^{\text{rank}}$) associate with expectations on the share of children with an abnormal level of behavioral problems (Appendix, Figure C.2) and self-reported gender norms (Appendix, Figure C.3). Overall, these beliefs measures strongly relate to behavioral expectations and self-reported liberal norms, suggesting they can serve as priors to help understand either homogeneous or heterogeneous responses to information. Finally, we find that expectations on GCSE pass rates only partially, but positively, associate with ${\theta_i}^{\text{graduate}}$ and ${\theta_i}^{\text{rank}}$ (Appendix, Figure C.4). Thus, as we discussed above, these GCSE expectations are weakly correlated with the θ_i^o measures, which remove differences in earnings potential between a mother and a father. The expectations on GCSE pass rates may capture a wider range of misinformation, uncertainty, or other dimensions, since earnings potential are not fixed and the question is asked in a more open way. In our next assessment of the information treatment effects, this gives us a useful way to distinguish belief updating around different dimensions in the priors.

4.2 Information Treatment Effects

We now assess whether information on children's performance when mothers work full-time is relevant to beliefs about the impact of mothers working full-time. We study information treatment effects on the following: (i) an incentivized quantitative scale about children's abnormal level of behavioral problems; (ii) responses to an open-ended

[28]This survey was opened on 25 July 2024 a week after the main survey. We kept it open until 27 July 2024.

question about what guided their answer to the quantitative scale; and (iii) self-reported gender norms. We finally turn to an extension on policy support, which includes a one-week follow-up.

4.2.1 Belief Updating

Information effects: approach. We look at three outcomes. On each of these, we estimate a treatment effect for the exposure to information about the GCSE pass rates when mothers work full-time hours given by the following:

$$y_i = \beta_0 + \gamma D_i + \sum_{j=1}^{J} \beta_j X_{ij} + \epsilon_i. \tag{3}$$

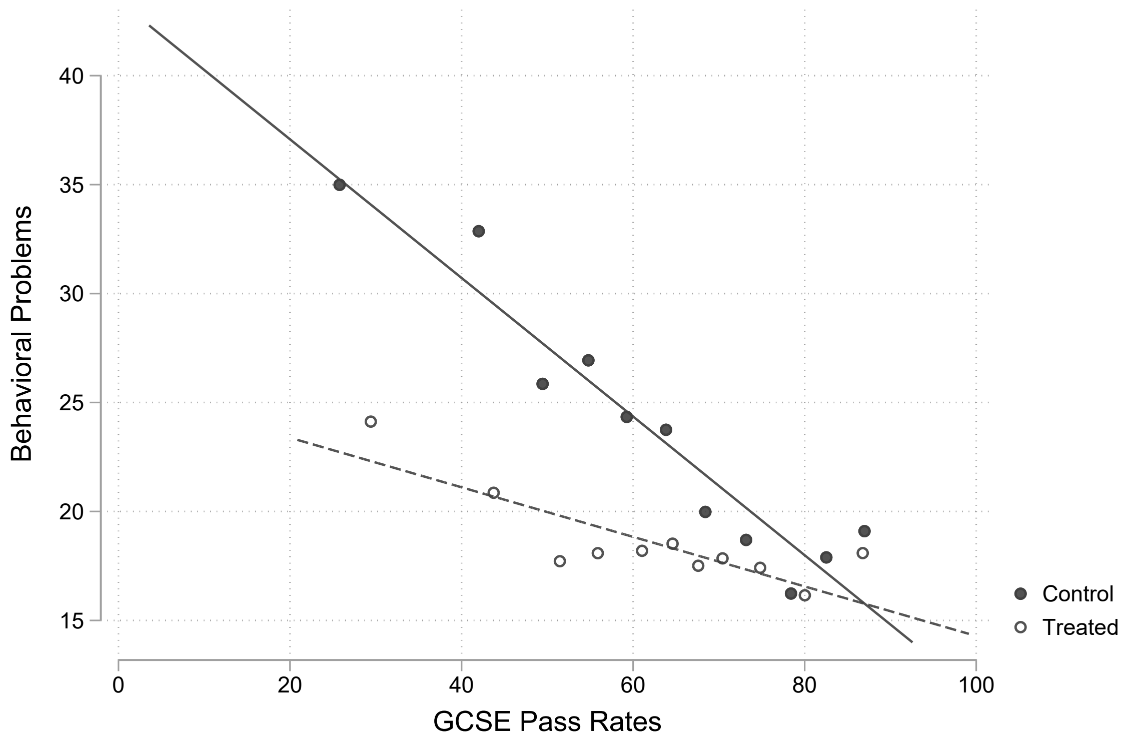
The outcome y_i is first the behavior beliefs for each individual i rescaled to lie between 0 and 1; second, the open ended harmful/not-harmful categorization; and third, the gender norms score with higher values representing more liberal norms. Exposure to the information treatment is captured by $D_i = 1$ and is otherwise equal to 0. X_{ij} is a vector of individual and pre-determined demographic variables.

We also test whether this information treatment effect is heterogeneous. To do this, we first disaggregate the information effect across under- and over-estimators of the GCSE initial beliefs, estimating equation (3) separately by these dimensions. Second, we repeat this exercise but use the hypothetical scenario-based individual beliefs (θ_i^o). Here, we split the sample by an indicator for whether a person has strictly negative perceptions relative to null or positive perceptions about mothers working longer hours. Later, we also look at heterogeneity around participants' characteristics and past experiences.

Information effects: results. We find that information leads to more positive perceptions on the impact of mothers working full-time. To show this, we start with Figure 2, splitting the sample by treatment status and plotting beliefs about behavior (the posterior) against expectations on GCSE pass rates. For control participants, there is a negative relationship between the two beliefs, meaning those who expect a low GCSE pass rate also expect higher shares of behavioral problems when mothers work full-time. Treated participants, however, show a weaker relationship between prior GCSE beliefs and the posterior, indicating a response to the information.

Next, in Table 8, we report the estimated effects of information based on equation (3). In Panel A, the outcome is beliefs about behavioral problems when mothers work full-time. The average response to information is a reduction (or improvement) in beliefs by about 5.2 percentage points (pp). In column group (2), we show that this information treatment effect is driven by participants who under-estimated GCSE pass rates. In column groups (3) and (4) respectively, we look at results split by participants' positive

Figure 2. Belief Updating in Response to the Information Treatment



Notes: This figure displays a binscatter plot of the expectations on behavioral problems against the initial GCSE pass rate beliefs split by treatment status.

versus negative perceptions on university graduation ($\theta_i{}^{\text{graduate}}$) and the expected earnings rank of the child at age 30 ($\theta_i{}^{\text{rank}}$) when mothers work longer hours. The information treatment is generally homogeneous across these groups.[29] Taken together, those who were wrong and below the true GCSE pass rate on average updated their beliefs regardless of their perceptions of absolute advantage captured in the θ_i^o measures. Moreover, in the Appendix, we report a homogeneous pattern of treatment effects across participants' characteristics (Table C.4), and past experiences (Table C.5). This is also confirmed by a mostly homogenous pattern in a causal forest (see the Appendix, Table C.6 Athey and Imbens, 2016; Athey and Wager, 2019), further suggesting that information can move beliefs.[30]

[29]Recall that the θ_i^o measures pinned down earnings potential between women and men and capture a particular portion of beliefs. Expectations on the GCSE pass rate may share variance with these measures but include other dimensions or simply uncertainty. When asking about the GCSE pass rate, we compare scenarios where mothers work longer versus shorter hours, controlling for similar education and income levels at household level. However, differences in earning potential among mothers with different working hours are not explicitly controlled for.

[30]Causal forests represent a machine learning approach to estimating heterogeneity. See Athey and Wager (2019) for an introduction and an application.

Table 8. Belief Updating and Information Effects

	(1) All Participants	(2) By GCSE Beliefs		(3) By θ^{graduate}		(4) By θ^{rank}	
		Under-	Over-	< 0	≥ 0	< 0	≥ 0
Panel A: Incentivized beliefs							
Treatment	-0.052***	-0.066***	-0.015	-0.065***	-0.041***	-0.069***	-0.037***
	(0.007)	(0.009)	(0.010)	(0.011)	(0.009)	(0.012)	(0.009)
Difference: *p*-value		0.000		0.090		0.028	
Mean Dep. Var	0.213	0.227	0.169	0.216	0.210	0.217	0.209
Panel B: Open Q: harmful/not harmful							
Treatment	-0.219***	-0.275***	-0.087	-0.210***	-0.233***	-0.247***	-0.195***
	(0.031)	(0.035)	(0.064)	(0.045)	(0.044)	(0.046)	(0.043)
Difference: *p*-value		0.009		0.716		0.406	
Mean Dep. Var	0.611	0.667	0.455	0.648	0.577	0.635	0.590
Panel C: Gender norms							
Treatment	0.546***	0.873***	-0.219	0.674**	0.448	0.420	0.631**
	(0.206)	(0.236)	(0.398)	(0.297)	(0.290)	(0.296)	(0.288)
Difference: *p*-value		0.017		0.582		0.606	
Mean Dep. Var	17.462	16.999	18.818	17.355	17.556	17.273	17.618
Participants	1056	787	269	493	563	477	579
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. This table presents OLS results of equation (3) each outcome listed in the panels. All specifications include controls for the pre-registered set of participants' characteristics. Results are presented (1) for the full sample of participants, (2) by under- and over-estimators of the GCSE initial beliefs, and by negative and positive values of (3) θ^{graduate} and (4) θ^{rank}.

In Panel B, we leverage the open-ended responses on what guided their answers to the quantitative question on behavioral problems. Our purpose here is to study whether participants are really thinking about and shifting views on what happens to children when mothers work full-time. We drop participants whose answers were unclear and could not be coded into either a harmful or a not-harmful category (141 unclear participants).[31] Information leads to a 22% decrease in the likelihood that participants' written answer expresses a harmful view (column 1). What participants write about strongly suggests their responses on the quantitative problem behavior scale truly capture their views on what happens to children when mothers work full-time. Additionally, when we split by prior belief measures, we see the same pattern of information effects in column groups (2) to (4) as we saw on the quantitative scale.

Our evidence shows that participants indeed respond to the provision of a simple fact about the GCSE pass rate when mothers work full-time. We further check whether the information moves people away from a mental model of lower time investments to children when mothers work full-time, which our evidence in Section 3.5 and Result 3 suggests should be a key channel respondents have in mind. Using the open-ended question, we construct a binary measure for respondents who expect lower time investments

[31] Later we will drop these from our analysis on beliefs as a robustness check (see Table C.2).

when mothers work full-time. In the Appendix, Table C.1, we report that information moves people away from this expectation with treated respondents 26% less likely than control members to expect lower time investments. Altogether, respondents think about the information and shift their views in response toward less harm for children and away from a model of reduced time investments when mothers work full-time.

To further corroborate that information leads to belief updating on views about mothers, we finally turn to a self-reported scale of gender norms about the role of mothers. In Table 8 and Panel C, we again find a similar pattern for the estimated information effects. Treated respondents express significantly more liberal views (column 1) and this is driven by GCSE under-estimators (column group 2). We again see evidence that the information response here is homogeneous across the θ_i^o measures, suggesting a degree of malleability in these beliefs. The magnitude of the effect is small relative to the mean, but this is reassuring that our information effect is yielding some thoughtful reflection and a small shift in views.

Information effects: robustness. We test whether our results on belief updating are robust to participants' uncertainty, their attention, risk of experimenter demand effects, and lack of clarity in their written answer to the open-ended question. In particular, experimenter demand effects would be a problem if respondents receiving the information try to give answers they think we want. While De Quidt et al. (2018) suggest that demand effects are minimal in practice, we try to rule these out by asking participants at the end of the survey to tell us what they think the survey was about in a text box open-ended entry. We classify those who appear to understand our focus on perceptions about mothers at work and children as at risk of a demand effect and drop them from the analysis.[32] Across all of of these checks, reported in columns (1) - (5) in the Appendix Table C.2, we find our results remain robust. We next re-weight our estimates based on the population weights discussed in Section 3.1, showing in column (6) that our results remain unchanged. Finally, we apply a post-double selection Lasso (Belloni et al., 2014) to the selection of pre-determined controls based on all possible variables we could use, showing in column (7) that again our conclusions hold.

Information effects and the degree of learning. GCSE under-estimators drive responses to information, but do they become more accurate? We now interact the infor-

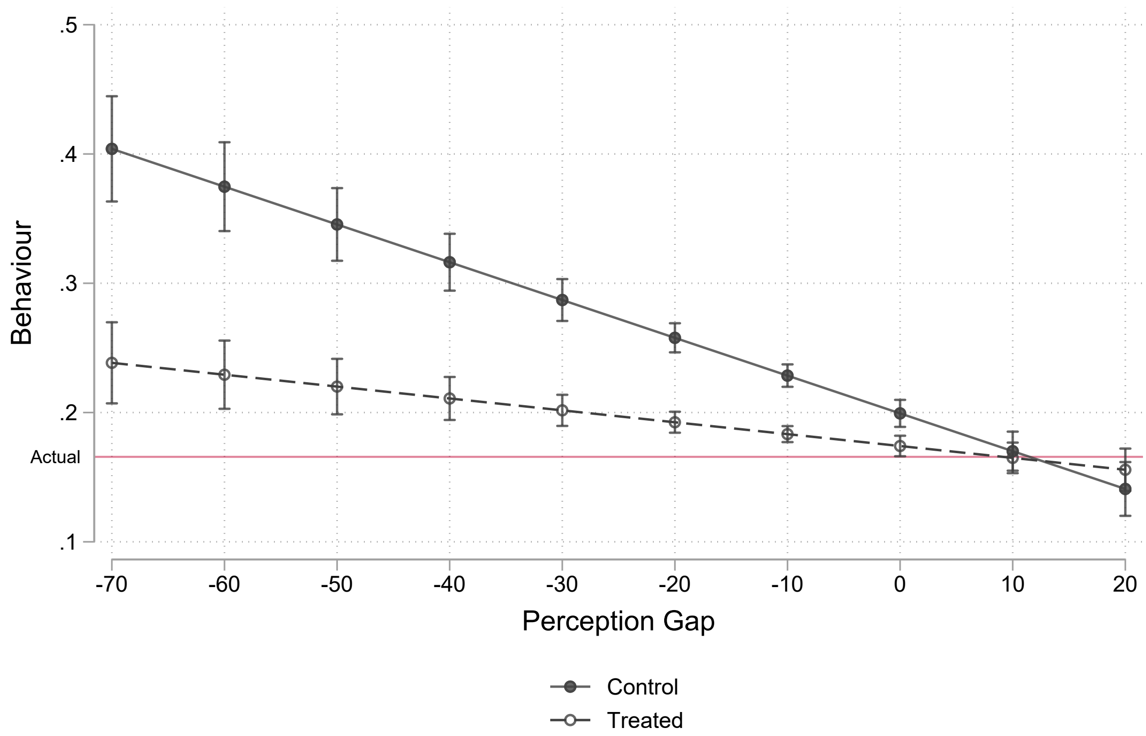
[32]We use a Random Forest Classifier to predict the risk of a demand effect, preprocessing text data by converting to lowercase, removing special characters, stop words, and HTML tags, and applying lemmatization. Text embeddings are generated using the pre-trained SentenceTransformer model (all-MiniLM-L6-v2) to capture semantic nuances. To address class imbalance, we used a pipeline with SMOTE and optimized hyper-parameters through GridSearchCV with StratifiedKFold cross-validation. We first trained the model on 30 classifications and then used it to predict labels for the remaining data. The model achieved an overall label prediction accuracy of 93.33%, highlighting the robustness of the classifier and preprocessing steps.

mation treatment with the perception gap (PG_i). This is the difference between the prior GCSE belief and the actual GCSE pass rate when mothers work full-time, *i.e.*, 75%. Participants with a positive perception gap are over-estimators on GCSE pass rates, while those with a negative gap are under-estimators. We use this, as in Haaland and Roth (2023), to assess the degree of learning in response to the information treatment. We look at the quantitative belief on behavioral problems and estimate the following specification:

$$y_i = \beta_0 + \beta_1 D_i + \beta_2 D_i \times PG_i + \beta_3 PG_i + \sum_{j=1}^{J} \beta_j X_{ij} + \varepsilon_i. \tag{4}$$

The regression results are reported in the Appendix, Table C.3, and in Figure 3, we report the visual representation of the results based on the full sample of participants (column 1 of Table C.3). Belief updating is stronger when a respondent's perception gap is more negative. Treatment moves respondents toward the correct answer, not away from it, with treated respondents becoming more accurate than the control group. We further split the results by beliefs on absolute advantage in Table C.3, and strikingly, we find that those who held stronger views on absolute advantage, as measured by negative θ_i^o measures, drive this accuracy update in response to information. Our evidence here is again reassuring that participants respond thoughtfully to the information.

Figure 3. Belief Updating and the Perception Gap



Notes: This figure displays means of the behavior belief across the distribution of the perception gap and over treatment status. Estimates are based on equation (4), for the full sample of participants.

Summary. We find clear evidence of belief updating in response to information. Our information treatment demonstrates that when mothers work full-time during the primary school years, children do at least just as well later on important GCSE exams compared to when mothers work part-time. Participants receiving the information move toward more positive perceptions of mothers working full-time regardless of their prior views on absolute advantage. Well tailored and delivered information then can be a useful tool to support accurate beliefs among parents on the impact of mothers working.

Result 4. *Information leads to belief updating on the effect of mothers working full-time reducing expectations on children's abnormal behavioral problems, leading to expressed views of less harm, and a shift toward more liberal gender norms on the role of mothers.*

4.2.2 Policy Support

We finally turn to expressed support for policy. In the main survey, we asked participants how strongly they agreed with support for policy to increase subsidized childcare and paternity leave policies. One-week later, in an obfuscated follow-up, we collected more views on policy support. These are about a proposal in the UK government to expand free childcare to 30 free hours per week for parents earning less than £60,000 per year and a proposal to create new nurseries in high-need areas by converting space in existing primary schools. Based on our pre-registration, these collected support measures on a 1 to 5 scale are split by the median to binary high/low support measures. We also asked participants how many hours of free childcare they would support to provide a more continuous scale (also pre-registered). The follow-up serves to both add more policy support questions and to offer another approach for limiting demand effects (Haaland et al., 2023).

Policy support: main survey. Our focus on a small fact as the information treatment, means that it is hard to expect large changes in policy views, as variation is likely more limited on agree or disagree type questions. Consistent with this, in the main survey, we do not see significant information effects on policy support, although, we do see some heterogeneous effects. On support for childcare policies we see flat nulls, although nearly 80% of participants agreed with this question. On support for paternity leave policies there is more variation to leverage (about 64% agree), and here we see suggestive evidence of a positive information effect. This positive effect on support is stronger and significant for GCSE under-estimators and those with views of absolute advantage in child rearing for women ($\theta_i^{\text{graduate}}$). Turning to heterogeneity by participants' characteristics (Appendix Table C.7) and past experiences (Appendix Table C.8) we are too under-powered to say much, but again, we see suggestive evidence of positive effects from information on support for paternity leave. This suggestion is particularly strong, though not significant, among females, those born outside the UK, university degree holders, part-time workers, and those with lower income. We point these out because they will show up again in the follow-up.

Table 9. Information Effects on Policy Support

	(1) All Participants	(2) By GCSE Beliefs		(3) By θ^{graduate}		(4) By θ^{rank}	
		Under-	Over-	< 0	≥ 0	< 0	≥ 0
Panel A: Subsidized childcare policies							
Treatment	-0.005	-0.012	0.014	0.044	-0.053	-0.038	0.017
	(0.024)	(0.029)	(0.046)	(0.035)	(0.033)	(0.037)	(0.033)
Difference: *p*-value		0.633		0.043		0.259	
Mean Dep. Var	0.804	0.795	0.829	0.811	0.798	0.805	0.803
Panel B: Paternity leave policies							
Treatment	0.040	0.066*	-0.022	0.089**	-0.008	0.039	0.041
	(0.029)	(0.034)	(0.056)	(0.042)	(0.041)	(0.044)	(0.040)
Difference: *p*-value		0.170		0.094		0.976	
Mean Dep. Var	0.638	0.624	0.680	0.657	0.622	0.644	0.634
Participants	1056	787	269	493	563	477	579
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. This table presents OLS results of equation (3) for two outcomes presented in separate panels. We consider two separate binary variable sets to one if the participant indicated a strong level of agreement (above the median) with subsidized childcare policies (panel A), and with paternity leave policies (panel B). All specifications include controls for the pre-registered set of participants' characteristics.

Policy support: follow-up survey. Finally, we discuss our last analyses based on the one-week follow-up. The outcomes are a continuous measure on the number of free childcare hours supported and two binary support measures on childcare policy and the conversion of existing primary schools into school-based nurseries. Results are in the Appendix and Tables C.10, C.11, and C.12. In Table C.10, we find no significant effects. We do find, however, that for the number of free childcare hours the information effect is suggestive of a positive effect. Next, in Table C.11, we find this information effect on free childcare hours is larger and significant for the same groups we saw suggestive evidence of policy support in the main survey. Information significantly increases the supported number of free childcare hours among women (1.7 hours higher), those born outside the UK (3.53 hours higher), and university degree holders (1.65 hours higher).[33] Strikingly, some of these groups were among those in Section 3 for whom we saw strong beliefs of absolute advantage.[34] Again, we interpret this as pointing toward the ability

[33]We also see insignificant but similar sized effects among part-time workers and those with lower income as we did in the main survey.

[34]Per our pre-registration, we also associated our measures of absolute advantage with these policy support measures at the follow-up using the information control group (Table C.9). The sample size with the control group is too small to reliably pick up links to these policy support measures where variation

of information to alleviate uncertainty for participants on the production of children's skills when mothers work.

We further look at heterogeneity on the binary support measures. Again, we see mainly null results. For support on converting existing space in primary schools to new nurseries, we even see some suggestive negative information effects, though none are significant. This measure, though, combines changing primary school space with nursery space potentially obfuscating views on support for mothers to work. This seems likely the case given our positive results on support for more free childcare hours. We also look at heterogeneity by participants' past experiences in Table C.12 with generally insignificant results but again a pattern of positive information effects on the number of free childcare hours. Overall, we must emphasize that our results on policy support are not strong. Nevertheless, they generally suggest information nudges policy views toward more support for women to be able to work.

5 Conclusion

In this paper, we study beliefs about children's skills when mothers work. Beliefs that mothers have an absolute advantage in child-rearing relative to men imply that gender gaps in labor markets will remain even as earnings potential is equalized across gender. We describe a target belief distribution as one that pins down earnings potential between a mother and father and captures differences in expectations for a child's future human capital between this mother or father working longer hours in the labor market. With a survey designed around vignettes of a family with a mother or father working longer hours, we elicit these beliefs on absolute advantage and show they are present and vary substantially over respondents.

Beliefs about women's absolute advantage are particularly predicted by those whose own-mother did not work full-time while they were growing up and among women who themselves had a strong employment motherhood penalty. Our evidence demonstrates that beliefs on absolute advantage are shaped by role model effects during formative childhood years, and it shows beliefs are highly correlated with the post-birth labor market trajectories of women consistent with gender norms and beliefs having an important effect on gender gaps.

Individuals' beliefs about the impact of mothers working likely stem from a mental model of mothers relative to fathers time use and productivity with children. To investigate this, we introduced new vignettes but randomized participants across features that let us test whether respondents have in mind expectations on differences in preferences between mothers and fathers for time investments into children's skills, differences in

can already be limited. We do see some positive link ($\theta_i{}^{\text{rank}}$ specifically, with the number of free childcare hours but do not interpret these strongly).

the productivity of investments, or differences in resource allocation or parental skill when mothers relative to fathers work longer hours.

The evidence points toward differences in preferences where participants expect that with equivalent time mothers will spend more time on skill investments with children than will fathers. Our analysis of a qualitative, open-ended question further demonstrates that when mothers work full-time participants largely tend to expect lower time investments into children. An important implication, is that mothers who are deciding whether to maintain a career may face pressure from expectations that their children will suffer from lower time investments. This is likely the most salient for families without the resources to pay for costly high quality childcare as a substitute, consistent with our evidence that beliefs on absolute advantage dissipate when we show respondents vignette scenarios with overall higher household resources.

Finally, we investigate whether factual information about children's outcomes when mothers work full-time will lead people to reduce expectations of harm for children. Our information treatment effects show that indeed participants respond to this information when they initially under-estimated outcomes. Treated respondents move toward more accurate expectations and in their qualitative responses demonstrate a lower expectation of harm for children. Thus, there is a role for policy to target misinformation about how well children do when mothers work.

Brought together this paper forms a broad profile of evidence on beliefs about children when mothers work. It gives empirical weight to the idea that beliefs influence gender gaps in labor markets through a new approach to elicit these beliefs. Thus, policy solely focused on equalizing earnings potential may remain ineffective for closing gender gaps. Moreover, we are able to show how these beliefs vary across the population and the mental models that can inform them. These mental models then create targets for policy effort to reduce uncertainty and misinformation. Our evidence on responses to the information treatment is then encouraging and suggests room for belief updating.

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Appendix Map

A Theoretical Appendix

A.1 Model Solution

This appendix shows how our two results illustrated in figure 1 holds generally in our model framework. Specifically, we solve the model and show that (i) when $\gamma > 0$ and $\rho_m = \rho_f$, mothers supply less labor due to a comparative advantage in child-rearing, and (ii) when if $\gamma = 0$ and $\rho_m > \rho_f$, mothers supply less labor due to an absolute advantage in child-rearing.

Substituting in the budget constraint, we write the household's optimization problem as

$$HC(m^*, f^*, e^*) = \max_{m,f} \; m^{\rho_m} f^{\rho_f} \left[(1-\gamma)W(1-m) + W(1-f)\right]^{\rho_e}.$$

Taking logarithms and solving the first-order conditions gives:

$$\frac{\partial \log HC}{\partial m} = 0 \iff \frac{\rho_m}{m} = \frac{\rho_e(1-\gamma)}{(1-\gamma)(1-m)+(1-f)},$$
$$\frac{\partial \log HC}{\partial f} = 0 \iff \frac{\rho_f}{f} = \frac{\rho_e}{(1-\gamma)(1-m)+(1-f)}.$$

Combining these gives:

$$\frac{f^*}{m^*} = \frac{\rho_f}{\rho_m}(1-\gamma).$$

The two results follow directly from this optimality condition.

A.2 Model Extension

This section presents an extended version of our conceptual framework, adjusting the child human capital production function to allow for different substitutability between time and financial inputs and for diffrential returns to scale. Unlike our baseline model, this augmented version can capture the empirical observation that the effect of mothers working longer hours on child development diminishes as household earnings increase.

We start by showing the limitations of the baseline model in replicating this observation. Specifically, we demonstrate that models where time and money inputs are *q-complements* – such as our baseline model – cannot replicate the observed negative effect. A general child human capital production function featuring time inputs from each parent and earnings as inputs can be witten as $HC = f(T(m, f), e)$ where $T(m, f)$ represents the aggregation of parental time inputs in domestic work, and e is earnings. We assume that f is increasing in both inputs. Time and earnings are considered *q-complements* if the marginal productivity of one input rises with the level of the other, i.e. $\frac{\partial^2 f}{\partial T \partial e} > 0$.

Let h_ℓ and h_s represent long hours and short hours at-home, respectively. As before, we define our empirical target θ as

$$\theta := f(T(\underbrace{h_s, h_\ell}_{MWL=1}), e) - f(T(\underbrace{h_\ell, h_s}_{MWL=0}), e).$$

Since f is increasing in T, we have $\theta < 0$ if and only if $T(MWL = 1) < T(MWL = 0)$. Our empirical finding is that for cases with $\theta < 0$ we observe $\frac{\partial\theta}{\partial e} > 0$. However, in the model

$$\frac{\partial\theta}{\partial e} = \frac{\partial f(T(MWL = 1), e)}{\partial e} - \frac{\partial f(T(MWL = 0), e)}{\partial e}$$

which is *negative* if $\frac{\partial^2 f}{\partial T \partial e} > 0$.

To reconcile the model with the data, we propose an augmented model incorporating a CES (Constant Elasticity of Substitution) aggregator for time and earnings inputs, with a parameter to control returns to scale. The revised human capital function is given by:

$$HC = ((m^{\rho_m} f^{\rho_f})^\sigma + e^\sigma)^{\alpha/\sigma},$$

where $\sigma \in (-\infty, 1)$ governs the substitutability between T and e while $\alpha \in (0, \infty)$ governs the returns to scale with respect to T and e. Using this definition, we derive:

$$\frac{\partial\theta}{\partial e} = \alpha\left((h_s^{\rho_m} h_\ell^{\rho_f})^\sigma + e^\sigma\right)^{\frac{\alpha}{\sigma}-1} e^{\sigma-1} - \alpha\left((h_\ell^{\rho_m} h_s^{\rho_f})^\sigma + e^\sigma\right)^{\frac{\alpha}{\sigma}-1} e^{\sigma-1}.$$

Thus, $\frac{\partial\theta}{\partial e} > 0$ if and only if

$$\left((h_s^{\rho_m} h_\ell^{\rho_f})^\sigma + e^\sigma\right)^{\frac{\alpha}{\sigma}-1} > \left((h_\ell^{\rho_m} h_s^{\rho_f})^\sigma + e^\sigma\right)^{\frac{\alpha}{\sigma}-1}.$$

After some manipulation it is clear that three parameter ranges are relevant for evaluating this inequality.

$$\begin{cases} \text{If } \sigma < 0 \text{ or } 0 < \sigma < \alpha & \text{we require } h_s^{\rho_m - \rho_f} > h_\ell^{\rho_m - \rho_f}. \\ \text{If } \sigma > \alpha & \text{we require } h_s^{\rho_m - \rho_f} < h_\ell^{\rho_m - \rho_f}. \end{cases}$$

Since $h_\ell > h_s$ and $\rho_f > \rho_m$ (indicating $\theta < 0$ — women hold an absolute advantage in domestic work), only the second inequality holds. We conclude that θ is increasing in earnings if and only if $\sigma < \alpha$, i.e. if the degree of substitutability between time and earnings is greater than the degree of returns to scale. Since σ is bounded above by 1 this requires that T and e are both gross substitutes ($\sigma > 0$) and that there is decreasing returns to scale ($\alpha < 1$).

B Hypothetical Beliefs Elicitation: Additional Results

B.1 Sample

Table B.1. Sample Representativeness

	National Population		Sample		Sample	
	Mean	SE	Unweighted Mean	SE	Weighted Mean	SE
Gender*						
Man	0.46	0.01	0.50	0.02	0.48	0.02
Woman	0.54	0.01	0.50	0.02	0.52	0.02
Age	43.69	0.22	38.46	0.22	40.98	0.35
Born in the UK	0.90	0.12	0.82	0.01	0.91	0.01
Ethnicity						
Asian	0.10	0.01	0.08	0.01	0.06	0.01
Black	0.04	0.00	0.10	0.01	0.04	0.01
Mixed	0.02	0.00	0.02	0.00	0.02	0.01
White	0.83	0.01	0.80	0.01	0.86	0.02
Other	0.01	0.00	0.01	0.00	0.01	0.00
Education						
No qualification	0.03	0.00	0.00	0.00	0.00	0.00
Other	0.05	0.01	0.01	0.00	0.05	0.01
GCSE or equivalent	0.19	0.01	0.10	0.01	0.22	0.02
A-levels or equivalent	0.21	0.01	0.23	0.01	0.22	0.02
Degree or higher	0.52	0.01	0.66	0.01	0.51	0.02
Monthly net income (£)						
0-500	0.12	0.01	0.08	0.01	0.13	0.02
500-1000	0.09	0.01	0.06	0.01	0.10	0.01
1000-1500	0.16	0.01	0.12	0.01	0.15	0.02
1500-2000	0.17	0.01	0.19	0.01	0.18	0.02
2000-2500	0.16	0.01	0.20	0.01	0.15	0.02
2500-3000	0.11	0.01	0.12	0.01	0.11	0.02
3000+	0.18	0.01	0.09	0.01	0.07	0.01
Single parent	0.17	0.01	0.12	0.01	0.20	0.02
Number of children aged 0-16*	1.52	0.02	1.78	0.03	1.83	0.04
Participants	6237		1056		1056	

Notes: Means and standard errors (SE) of the key demographic information for a nationally representative sample (column 1) as well as for our survey participants (column 2). The national population figures are drawn from the relevant population of respondents to the 2022 Understanding Society wave, and weighted using the corresponding cross-sectional weight. The * indicates variables targeted through our sampling approach. See paragraph below for the description of our sample's weighting approach.

Weighting approach. For some dimensions, our sample is different from the corresponding national population distribution of parents in England. In particular, those who hold a degree or higher are over-represented in our sample, and lower income categories are under-represented. Also, we find that our sample's average age, the shares of individuals born in the UK, and the share of single parents are somewhat lower than the national distribution. For all categories, we construct respective initial weights corresponding to the national population proportion divided by that in the sample. For instance, the weight for holding a degree or higher is equal to $w_{degree} = \frac{0.5248}{0.6553}$, while the weight for no qualification is $w_{none} = \frac{0.0275}{0.009}$, etc., and we use 4-digit proportions to avoid zeros. As age is a continuous variable, we normalize its weight to lay on a scale from 0 to 1. Finally, we combine these initial weights for participants by multiplying all initial weights w_d.

Table B.2. Participants' Descriptive Statistics

	Treated	Control	Diff.	Overall
Gender				
Man	0.48	0.51	-0.03	0.50
Woman	0.52	0.47	0.05	0.50
Age	38.14	38.79	-0.65	38.46
Born in the UK	0.83	0.82	0.01	0.82
University graduate	0.66	0.65	0.00	0.66
Ethnicity				
Asian	0.06	0.09	-0.03	0.08
Black	0.11	0.09	0.02	0.10
Mixed	0.03	0.02	0.01	0.02
White	0.79	0.80	-0.00	0.80
Other	0.01	0.01	0.01	0.01
Vote at last UK General Election				
Conservative	0.10	0.10	0.00	0.10
Labour	0.46	0.48	-0.02	0.47
Liberal Democrat	0.11	0.10	0.02	0.10
Green Party	0.07	0.07	-0.00	0.07
Reform UK	0.09	0.08	0.01	0.09
Other	0.02	0.03	-0.02	0.02
None	0.16	0.14	0.01	0.15
Full-time employment	0.60	0.64	-0.04	0.62
Weekly hours worked	31.05	32.68	-1.63	31.86
Monthly net income (£)				
Low	0.46	0.45	0.02	0.45
Medium	0.33	0.31	0.02	0.32
High	0.21	0.25	-0.04	0.23
Single parent	0.12	0.13	-0.02	0.12
Number of children aged 0-16	1.78	1.78	-0.00	1.78
Partner's monthly net income (£)				
No partner	0.06	0.08	-0.02	0.07
Low	0.36	0.34	0.02	0.35
Medium	0.40	0.39	0.01	0.39
High	0.25	0.27	-0.02	0.26
Participants	525	531		1056

Notes: This table displays the means of the key demographic information for our survey participants, by treatment status. Differences are statistically significant at the following levels: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Note that six respondents listed "other" or "prefer not to say" for gender. For the participant's and the partner's (if any) monthly net income, we group the categories into tertiles. For the participant's income, "Low" encompasses income between 0 and £2,000,"Medium" considers income between £2,000 and £3,000, while "High" corresponds to monthly net income greater than £3,000. For the partner's, we construct tertiles of the original variable and for those who have a partner. The "Low" category corresponds to incomes between 0 and £1,500, the "Medium" category corresponds to incomes between £1,500 and £3,000, while the "High" category is for incomes above £3,000.

B.2 Hypothetical Beliefs Elicitation

Table B.3. Randomization in Set-Up

	Mean	SD	N
Child is a girl (vs. boy)	0.49	0.50	517
Child is aged 4 (vs. 10)	0.51	0.50	542
SSE_i: 20% (vs. 10%)	0.51	0.50	540

Notes: Total number of participants = 1056. This table presents descriptive statistics for the randomization in set-up. For instance, 49% of our sample (*i.e.*, 517 participants) got displayed, in the hypothetical scenarios, a boy child. SSE_i refers to the share of income spent on the child's educational and extracurricular activities.

Table B.4. Heterogeneity in Beliefs by Participants' Characteristics

	Median Age		Gender		Ethnicity		Born in the UK		University Degree		Working Hours		Participant's Income		Number of Children		Vote at last UK General Election		
	≥ 38	< 38	Female	Male	White	Non-white	Yes	No	Yes	No	FT	PT or none	≥ Median	< Median	< 2	≥ 2	Conservative	Liberal	Other or None
$\mathbb{P}$(graduate): $MWL_{j=1}$	-1.11***	-0.73	-0.86*	-1.02**	-0.59*	-2.26***	-0.63**	-2.37***	-1.15***	-0.52	-0.87**	-1.04**	-0.59	-1.65***	-0.97**	-0.89**	-0.94	-0.73*	-1.69***
	(0.39)	(0.46)	(0.45)	(0.40)	(0.32)	(0.79)	(0.31)	(0.88)	(0.37)	(0.51)	(0.37)	(0.50)	(0.36)	(0.53)	(0.40)	(0.44)	(0.74)	(0.38)	(0.63)
Earnings Rank: $MWL_{j=1}$	-0.64*	-0.70*	-0.36	-0.97***	-0.48*	-1.40*	-0.48*	-1.56**	-0.69**	-0.63	-0.44	-1.04**	-0.37	-1.29***	-0.74**	-0.57	-1.14*	-0.24	-1.76***
	(0.36)	(0.40)	(0.40)	(0.36)	(0.28)	(0.73)	(0.28)	(0.78)	(0.33)	(0.45)	(0.33)	(0.46)	(0.33)	(0.47)	(0.37)	(0.39)	(0.67)	(0.32)	(0.66)
Participants	563	493	525	525	840	216	871	185	692	364	657	399	712	344	613	443	194	679	183
Observations	3378	2958	3150	3150	5040	1296	5226	1110	4152	2184	3942	2394	4272	2064	3678	2658	1164	4074	1098
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scenario Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Standard errors are clustered on individuals. Each coefficient is obtained from separate OLS regressions estimating equation (2) on the subsample defined by the displayed label and for our two expected outcomes: (i) the probability for the child to graduate ($\mathbb{P}$(graduate)), and (ii) the earnings rank of the child at age 30 (Earnings Rank). "FT" stands for full-time, while "PT" stands for part-time.

Table B.5. Heterogeneity in Beliefs by Participants' Past Experiences

	Own-Mothers' FT Employment				By the Median Motherhood Penalty	
	Yes: when you were < 12	No: when you were < 12	Yes: when you were ≥ 12	No: when you were ≥ 12	≥ | Median Penalty |	< | Median Penalty |
$\mathbb{P}$(graduate): $MWL_{j=1}$	-0.54	-1.13***	-0.93**	-1.02**	-1.42**	-0.05
	(0.58)	(0.35)	(0.46)	(0.40)	(0.60)	(0.68)
Rank: $MWL_{j=1}$	0.24	-1.07***	-0.38	-0.96***	-1.09*	0.40
	(0.49)	(0.32)	(0.40)	(0.36)	(0.57)	(0.58)
Participants	339	708	494	547	261	253
Observations	2034	4248	2964	3282	1566	1518
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Scenario Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Standard errors are clustered on individuals. Each coefficient is obtained from separate OLS regressions estimating equation (2) on the subsample defined by the displayed label and for our two expected outcomes: (i) the probability for the child to graduate ($\mathbb{P}$(graduate)), and (ii) the earnings rank of the child at age 30 (Earnings Rank). "FT" stands for full-time, while "PT" stands for part-time. For participants' own-mothers' employment during the participant's childhood (own-mother's employment: < 12), and adolescence (own-mother's employment: ≥ 12), we drop observations that were listed as not applicable ($N = 16$). We also collected this information for their father's, but 93% had a full-time working father when they were less than 12, and 90% when they were adolescents. Thus, we do not report results due to small cell sizes for the part-time or less category. Finally, we calculated each woman's motherhood employment penalty relative to men. The median of this distribution is approximately a -18 percent drop in the likelihood of FT employment after childbirth. We split the sample by women with a high penalty (a ≥ absolute value of the median penalty) or a low penalty (< absolute value of the median penalty).

Table B.6. Heterogeneity in Beliefs by Design Features

	Child's Gender		Child's Age		SSE		Working Hours Profile		Wage Profile		First Shown	
	Girl	Boy	4	10	SSE: 20%	SSE: 10%	FT–FT	FT–PT	Higher	Lower	Mother	Father
$\mathbb{P}$(graduate): $MWL_{j=1}$	-0.57	-1.28***	-1.11***	-0.75*	-0.53	-1.36***	-0.57	-1.30***	-0.45	-1.50***	-0.29	-1.59***
	(0.43)	(0.41)	(0.41)	(0.44)	(0.41)	(0.44)	(0.42)	(0.42)	(0.40)	(0.45)	(0.43)	(0.41)
Earnings Rank: $MWL_{j=1}$	-0.41	-0.91**	-0.66*	-0.68*	-0.59	-0.75*	-0.56	-0.78**	-0.34	-1.05**	-0.34	-1.00***
	(0.37)	(0.38)	(0.37)	(0.39)	(0.36)	(0.39)	(0.38)	(0.38)	(0.34)	(0.43)	(0.39)	(0.36)
Participants	517	539	542	514	540	516	533	523	567	489	532	524
Observations	3102	3234	3252	3084	3240	3096	3198	3138	3402	2934	3192	3144
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scenario Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Standard errors are clustered on individuals. We estimate equation (2) for each feature, *i.e.*, when the hypothetical child is a girl, a boy, is 4, etc. and report here the $\hat{\delta}$ associated with $MWL_{j=1}$ for each of those regressions. The FT–FT design presents both parents as full-time with one working longer hours (42 vs. 35), while the FT–PT design presents a full-time parent *versus* a part-time parent (36 vs. 20). The "first shown" column corresponds to the set of scenarios shown first to the participant — either $MWL = 1$ (mother works longer hours) or $MWL = 0$ (father works longer hours) in the beliefs elicitation survey.

Table B.7. Robustness — Beliefs about Mothers Working Longer

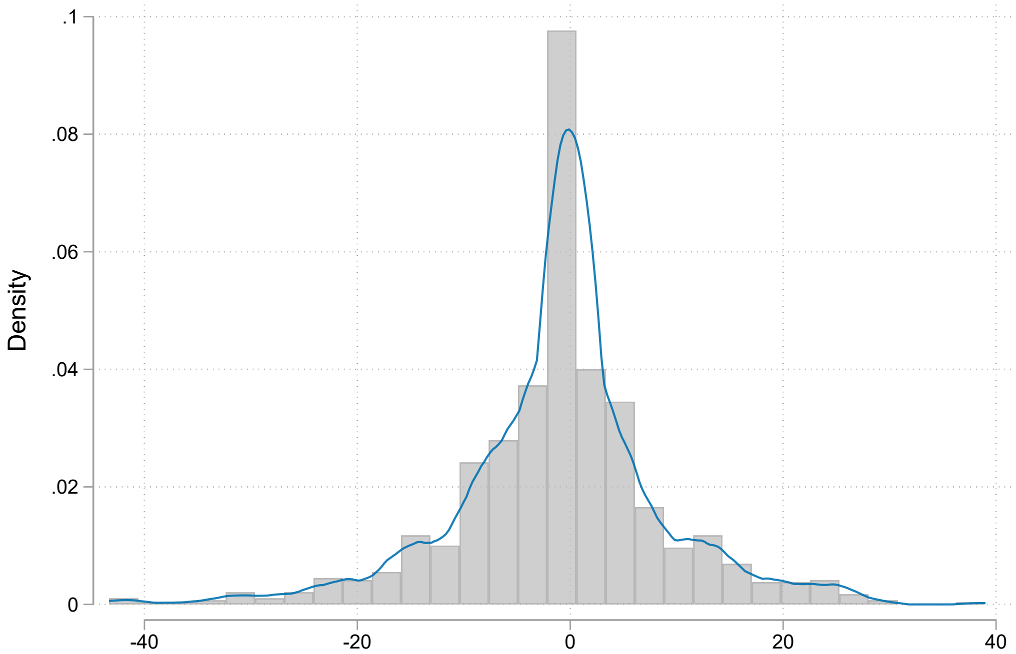
	(1) At Least Somewhat Certain		(2) Screener		(3) Response Time		(4) Re-Weighting	
	$\mathbb{P}$(graduate)	Earnings Rank	$\mathbb{P}$(graduate)	Earnings Rank	$\mathbb{P}$(graduate)	Earnings Rank	$\mathbb{P}$(graduate)	Earnings Rank
$MWL_{j=1}$	-1.230***	-0.870***	-0.717**	-0.556**	-0.925***	-0.736***	-0.788**	-0.840**
	(0.360)	(0.322)	(0.300)	(0.270)	(0.313)	(0.283)	(0.377)	(0.356)
Mean Dep. Var	56^{th}	47^{th}	56^{th}	52^{nd}	56^{th}	49^{th}	55^{th}	49^{th}
Participants	795	261	1003	53	950	950	1056	1056
Observations	4770	1566	6018	318	5700	5700	6336	6336
Individual Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Scenario Income Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. OLS results for equation (2) — including individual and scenario income fixed effects — on the expected probability for the child to graduate ($\mathbb{P}$(graduate)), and the percentile ranking expected for the child at age 30 among other 30 year olds (Earnings Rank). Standard errors are clustered on individuals. We present results for four checks in four distinct blocks of columns. In (1), we restrict the sample to participants at least somewhat certain about their answer to the hypothetical scenarios, while in (2), we keep participants who passed the "turquoise" screener discussed in Subsection 3.2. In (3), we drop participants with the lowest and highest 5% response times, and in (4) we re-weight our sample to match the national population distribution (see Subsection B.1).

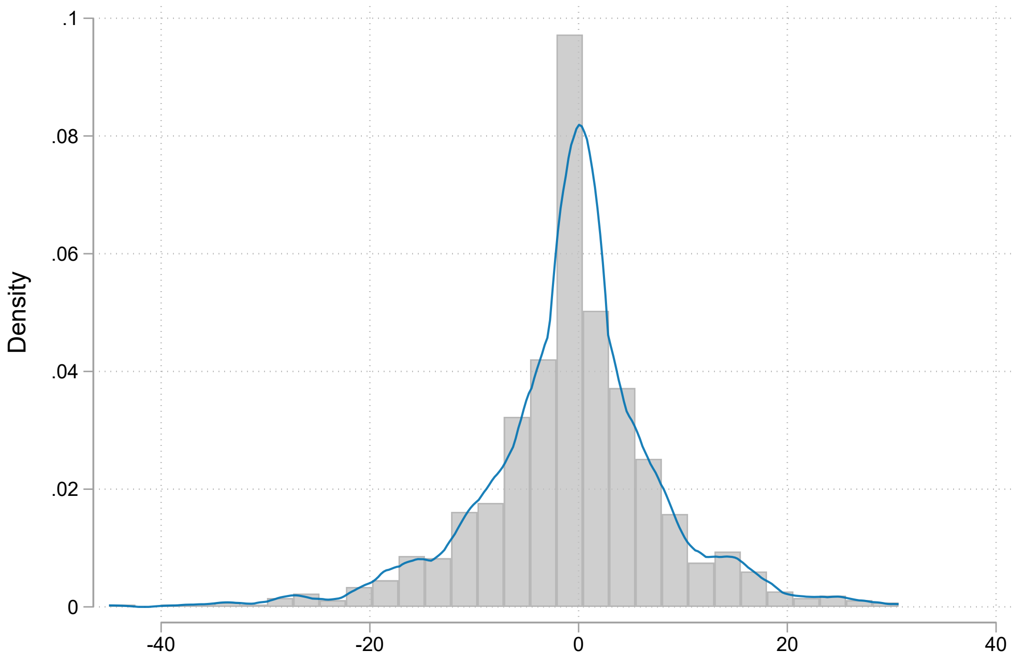
B.3 Individual Perceptions

Figure B.1. Distribution of Perceived Returns

(a) Perceived Returns: θ^{graduate}

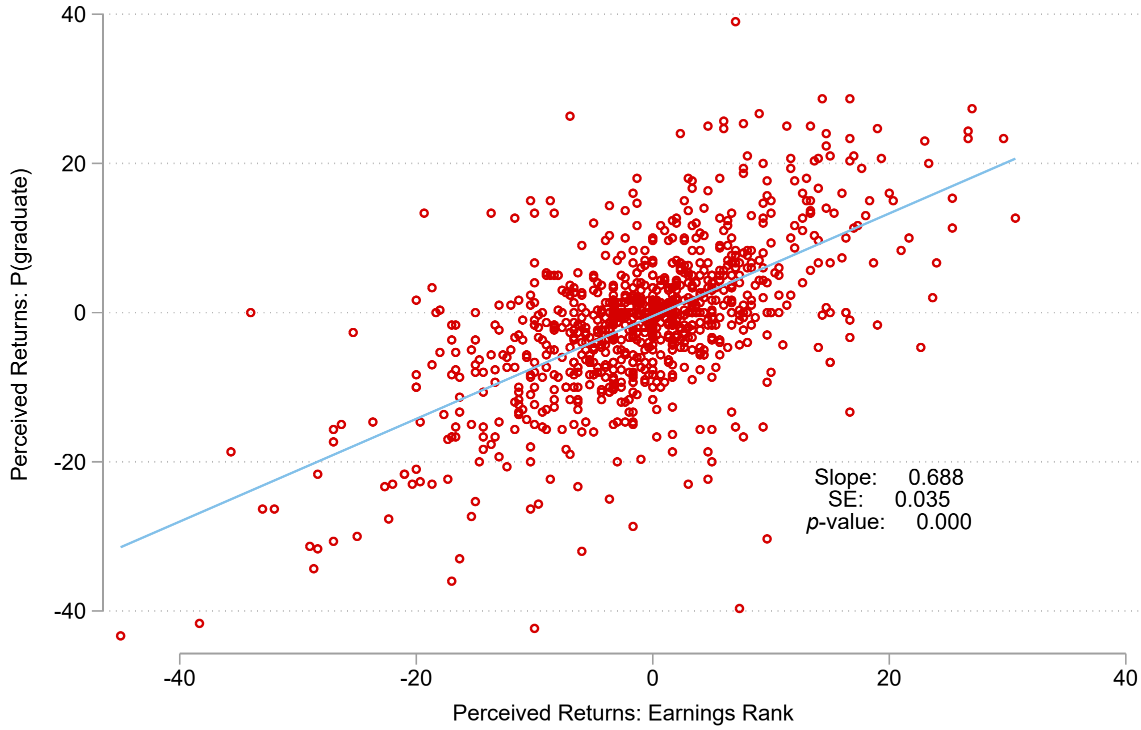


(b) Perceived Returns: θ^{rank}



Notes: $N = 249$. Distribution of our two perceived returns with kernel density plot over (a) the probability for the child to graduate from university (θ^{graduate}), and (b) the expected earnings rank of the child at age 30 (θ^{rank}).

Figure B.2. Relationship of Individual-Level Beliefs Measures



Notes: This figure presents a scatter plot with a line of best fit for our individual-level perceptions over the probability of graduating from university (θ^{graduate}) on the y-axis, and the earnings rank of the child at age 30 (θ^{rank}) one the x-axis.

Table B.8. Relationship Between Beliefs and Participants' Behavior

	Skills Time			Outdoors Time			ln(Hours Worked)		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Control group									
θ^{graduate}	0.003		0.008	0.020***		0.020***	0.001		0.001
	(0.006)		(0.007)	(0.005)		(0.007)	(0.002)		(0.002)
θ^{rank}		-0.005	-0.010		0.012**	-0.001		0.002	0.001
		(0.006)	(0.007)		(0.005)	(0.006)		(0.002)	(0.002)
Observations	3186	3186	3186	3186	3186	3186	3186	3186	3186
Participants	531	531	531	531	531	531	531	531	531
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel B: Women	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
θ^{graduate}	-0.022***		-0.018**	0.008		0.005	-0.002		-0.002
	(0.007)		(0.009)	(0.007)		(0.009)	(0.002)		(0.003)
θ^{rank}		-0.020**	-0.007		0.009	0.005		-0.002	-0.000
		(0.009)	(0.011)		(0.007)	(0.010)		(0.003)	(0.004)
Observations	1656	1656	1656	1656	1656	1656	1656	1656	1656
Participants	276	276	276	276	276	276	276	276	276
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Panel C: Men	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
θ^{graduate}	0.048***		0.059***	0.040***		0.045***	0.006***		0.005***
	(0.008)		(0.009)	(0.008)		(0.010)	(0.002)		(0.002)
θ^{rank}		0.009	-0.021**		0.013*	-0.010		0.004**	0.002
		(0.009)	(0.009)		(0.007)	(0.009)		(0.002)	(0.002)
Observations	1530	1530	1530	1530	1530	1530	1530	1530	1530
Participants	255	255	255	255	255	255	255	255	255
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: p <0.10; ** p <0.05, *** p <0.01. Standard errors, in parentheses, are bootstrapped with 1,000 replications. We run OLS regressions on three main outcomes reflecting participant's behavior with their child(ren) and on the labor market for the control group only. Specifically, these regressions look at the associations between the participant's behavior and (1) their perceived returns over the probability for the child to graduate (θ^{graduate}), (2) the expected earnings rank of the child at age 30 (θ^{rank}), and (3) both dimensions. Skills Time (resp., Outdoors Time) corresponds to the number of hours spent per day by the participant helping their child(ren) develop their skills (resp., doing outdoors activities with them). ln(Hours Worked) corresponds to the log of the participant's weekly number of hours worked. Individuals controls include participant's gender (for Panel A), a quadratic in age, an indicator for whether they have at least a university degree, employment status (full-time *versus* part-time or less), and ethnicity (white *versus* non-white). Six participants listed "other" or "prefer not to say" for gender. We code these as 0 and control for an indicator flagging them in Panel A, and exclude them in Panels B and C. The number of participants does not vary between panels as those six participants belong to the treatment group.

B.4 Mechanisms for Variation in Beliefs

Table B.9. Outcomes Descriptive Statistics

	Mean	SD	Min	Max	N
Minutes spent helping the child					
Prepare for the test	149.24	116.05	0.00	600.00	1056
Doing extracurricular activities	161.06	112.01	0.00	600.00	1056
Expected rank at the test	0.42	0.20	0.01	0.99	1056
Mother: $\mathbb{P}$(University Graduate)	0.51	0.22	0.00	1.00	1056
Father: $\mathbb{P}$(University Graduate)	0.46	0.22	0.00	1.00	1056
Share of income spent on extracurricular activities	0.18	0.15	0.00	0.97	1056

Notes: This table displays descriptive statistics for the outcomes collected to investigate the mechanisms in variation in beliefs, introduced in Subsection 3.5.

Table B.10. Expectations on Resource Allocation and Parental Education by Elicited Beliefs

	(1)	(2)	(3)	(4)
	By θ^{graduate}		By θ^{rank}	
	< 0	≥ 0	< 0	≥ 0
Panel A: Resource Allocation				
Mother Earns More	0.001	0.012	-0.003	0.016
	(0.013)	(0.011)	(0.013)	(0.012)
Panel B: $\mathbb{P}$(University Graduate) Difference (Mother – Father)	(1)	(2)	(3)	(4)
Works Full-Time	0.050	0.019	0.042	0.023
	(0.035)	(0.032)	(0.037)	(0.030)
Participants	493	563	477	579
Individual Controls	Yes	Yes	Yes	Yes

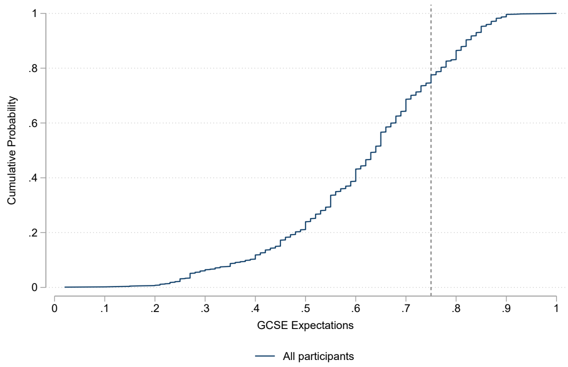
Notes: p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. All specifications include controls for the pre-registered set of participants' characteristics.

C Information Treatment: Additional Results

C.1 Belief Updating

Figure C.1. CDF of Incentivized Beliefs

(a) GCSE Pass Rates

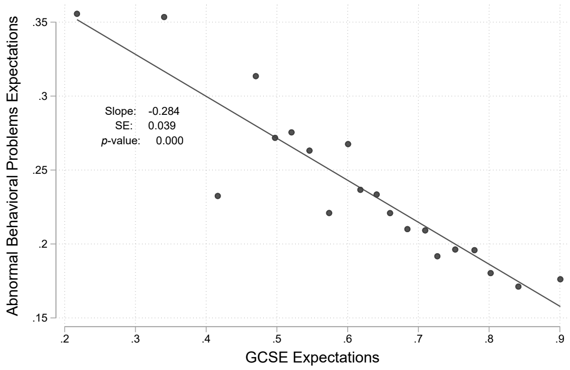


(b) Behavioral Problems

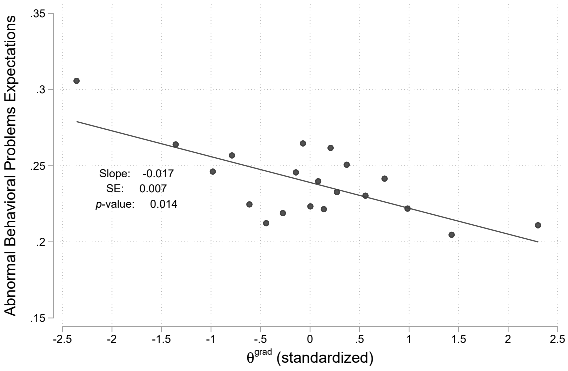
Notes: Figure (a) shows the cumulative distribution function for beliefs about the passing rate of 5 or more GCSEs (with at least C/4) in families where mothers work 35 hours or more per week. Figure (b) also reports the cumulative distribution function, but for beliefs about the share of children having an abnormal level of behavioral problems when the mother works full-time, using only control group respondents. In both panels, the short-dashed lines respectively indicate the true levels of (a) for GCSE pass rates (75%), and (b) behavioral problems (17%).

Figure C.2. Associations of Beliefs Measures and the Posterior

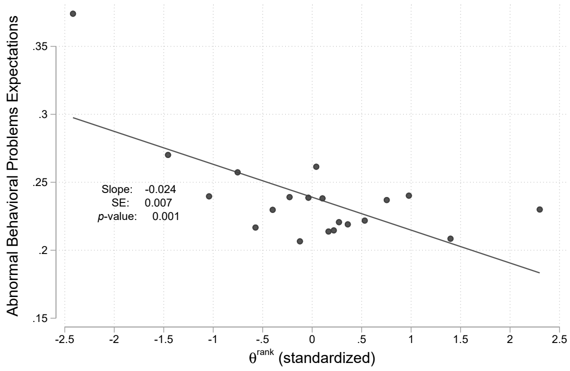
(a) Expectations on GCSE pass rates



(b) Expectations on $\mathbb{P}$(graduate)



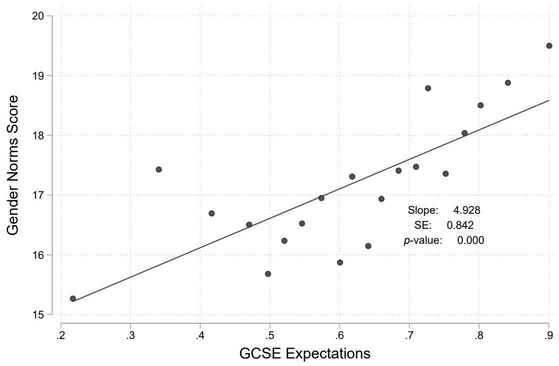
(c) Expectations on Earnings Rank



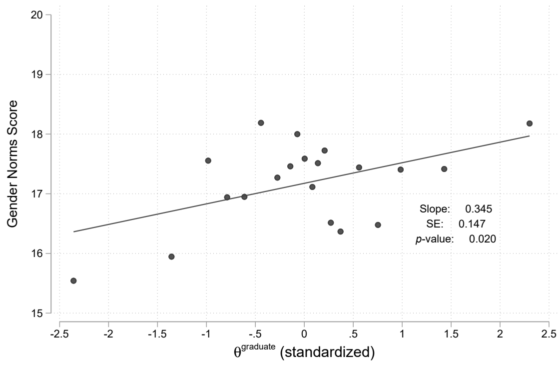
Notes: These figures present binscatter plots to highlight the relationships between the posterior belief, expectations on abnormal behavioral problems when mothers work full-time, and (a) the expectation for GCSE pass rates when mothers work full-time ($GCSE_i$), (b) expectations on the child's probability to graduate from university on the expected probability for the child to graduate ($\theta_i{}^{\text{graduate}}$), and (c) the expected earnings rank of the child at age 30 ($\theta_i{}^{\text{rank}}$). In (b) and (c) we standardize the θ_i^o measures around 0 with an standard deviation of 1. We always control for participant characteristics, and we only use the information treatment control group for this analysis ($N = 531$).

Figure C.3. Associations of Beliefs Measures and Gender Norms

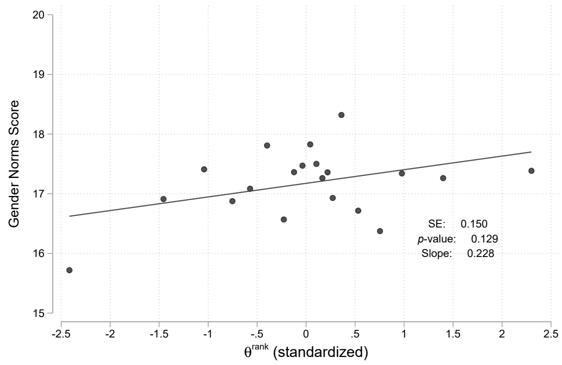
(a) Expectations on GCSE pass rates



(b) Expectations on $\mathbb{P}$(graduate)



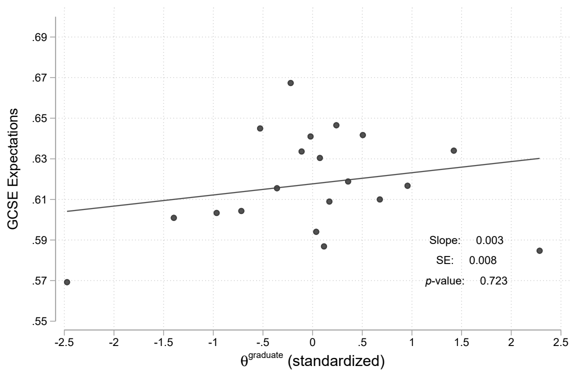
(c) Expectations on Earnings Rank



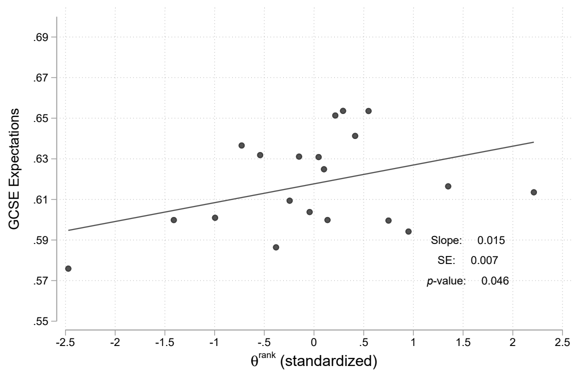
Notes: These figures present binscatter plots to highlight the relationships between gender norms and (a) the expectation for GCSE pass rates when mothers work full-time ($GCSE_i$), (b) expectations on the child's probability to graduate from university on the expected probability for the child to graduate (${\theta_i}^{\text{graduate}}$), and (c) the expected earnings rank of the child at age 30 (${\theta_i}^{\text{rank}}$). These are for the control group only (N = 531). In (b) and (c), we standardize the θ_i^o measures around 0, and with a standard deviation of 1. All specifications include controls for the pre-registered set of participants' characteristics.

Figure C.4. Associations of GCSE Expectations and Elicited Beliefs

(a) Expectations on $\mathbb{P}$(graduate)



(b) Expectations on Earnings Rank



Notes: These figures present binscatter plots to highlight the relationships between the the expectation for GCSE pass rates when mothers work full-time ($GCSE_i$) and (a) expectations on the hypothetical child's probability to graduate from university (${\theta_i}^{\text{graduate}}$), and (b) expectations on the earnings rank of the child at age 30 (${\theta_i}^{\text{rank}}$), for the control group only (N = 531). We standardize the θ_i^o measures around 0, and with a standard deviation of 1. All specifications include controls for the pre-registered set of participants' characteristics.

Table C.1. Belief Updating: Additional Analysis with the Open-ended Question

	(1)	(2)
	Lower Time Investment	
Treatment	-0.259***	-0.252***
	(0.032)	(0.032)
Mean Dep. Var†	0.674	0.708
Participants	1056	915
Individual Controls	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. † The mean of the dependent variable is calculated for the control group only. This table presents our information treatment effect model (equation (3)), using as an outcome a binary indicator flagging respondents whose written answers suggest they expect lower time investments into children when mothers work full-time. We previously classified answers into five groups: Answers were classified into (i) "lower time investments" (ii) "better resources" (iii) "no relationship" (iv) "other" and (v) "unclear" from which we created the binary indicator for "lower time investment". Results in column (1) are for the full sample of participants, while in column (2), we drop participants whose answer was classified as "unclear".

Table C.2. Robustness: Belief Updating and Information Effects

	(1) At Least Somewhat Certain	(2) Screener	(3) Response Time	(4) Risk of Demand Effect	(5) Unclear Mechanism	(6) Re-Weighting	(7) PDS Lasso
Panel A: Incentivized beliefs							
Treatment	-0.053***	-0.052***	-0.059***	-0.047***	-0.049***	-0.050***	-0.060***
	(0.009)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.010)
Mean Dep. Var	0.217	0.209	0.209	0.215	0.211	0.208	0.213
Panel B: Open Q: harmful/not harmful							
Treatment	-0.211***	-0.220***	-0.235***	-0.189***	-0.219***	-0.221***	-0.247***
	(0.036)	(0.032)	(0.033)	(0.036)	(0.031)	(0.040)	(0.045)
Mean Dep. Var	0.630	0.607	0.614	0.610	0.611	0.620	0.611
Panel C: Gender norms							
Treatment	0.609**	0.486**	0.514**	0.399*	0.569**	0.596**	0.886***
	(0.240)	(0.213)	(0.219)	(0.228)	(0.223)	(0.244)	(0.278)
Mean Dep. Var	17.382	17.513	17.518	17.295	17.395	17.150	0.611
Participants	795	1003	950	796	915	1056	1056
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. This table presents OLS results of equation (3) for each outcome listed in the panels. In columns (1) and (2) respectively, we keep participants at least somewhat certain of their answers on the hypothetical vignettes, and who passed the "turquoise" screener. In the next columns, we drop participants (3) with the 5% lowest and highest response times, (4) more at risk of a demand effect, and (5) those whose answer was unclear to the open-ended question on what guided their answer about children with abnormal level of behavioral problems. Risk of demand effect was coded from an open question at end of the survey where respondents were asked what they thought the survey was about. We classify answers that allude to perceptions about mothers working and children as "at risk of a demand effect" and drop those (column 4) from the analysis. Finally, in (6), we re-weight our sample to match the national population distribution (see Subsection B.1), and in (7), we perform a PDS Lasso approach including all of participants' demographics for the control variables selection (Belloni et al., 2014).

Table C.3. Belief Updating and the Perception Gap by Prior Beliefs

	(1) All Participants	(2) By θ^{graduate}		(3) By θ^{rank}	
		< 0	≥ 0	< 0	≥ 0
Perception Gap × Treatment	0.002***	0.003***	0.001	0.003***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Perception Gap	-0.003***	-0.003***	-0.003***	-0.003***	-0.002***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Treatment	-0.024***	-0.025**	-0.025**	-0.027**	-0.023**
	(0.008)	(0.011)	(0.011)	(0.013)	(0.010)
Mean Dep. Var†	0.213	0.216	0.210	0.217	0.209
Participants	1056	493	563	477	579
Individual Controls	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. †The mean of the dependent variable is calculated for the control group only. This table shows OLS results of equation (4), where the outcome is the incentivized beliefs on the share of children out of 100 scoring above the threshold for abnormal behavioral problems when mothers work full-time. We rescaled this to lie between 0 and 1 for interpretation purposes. Results are presented (1) for the full sample of participants, (2) by negative and positive values of θ^{graduate} and (3) θ^{rank}. Individual controls follow our pre-registered set defined previously; however, this heterogeneity analysis here by prior beliefs was not pre-registered.

Table C.4. Heterogeneity in Information Treatment Effects on Incentivized Beliefs by Participant's Characteristics

	Median Age		Gender		Ethnicity		Born in the UK		University Degree		Working Hours		Household Income		Number of Children		Voted at last UK General Election		
	≥ 38	< 38	Female	Male	White	Non-white	Yes	No	Yes	No	FT	PT	≥ Median	< Median	< 2	≥ 2	Conservative	Liberal	Other or None
Treatment	-0.06***	-0.04***	-0.06***	-0.04***	-0.04***	-0.09***	-0.04***	-0.10***	-0.05***	-0.05***	-0.04***	-0.07***	-0.07***	-0.05***	-0.04***	-0.06***	-0.06***	-0.05***	-0.06***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)	(0.02)
Participants	563	493	525	525	840	216	871	185	692	364	657	399	261	253	613	443	194	679	183
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. We estimate separately equation (3) on the participant's posterior beliefs (about the share of children having an abnormal level of behavioral problems in families where the mother works full-time), for each participant's characteristic, *i.e.*, for when the participant is a man, a woman, has a degree, etc. We display here $\hat{\gamma}$ associated with D_i for each of these regressions. Estimates for other genders than male and female not displayed due to sample size issues. The outcome is rescaled to lie between 0 and 1. For the columns "Vote at last UK General Elections", we asked participants: "Which party did you choose as your primary vote in the last UK General Election?" and provided them with a list of candidate parties. We condensed information into three categories as follows: Conservative Party and Reform UK; Labour, Liberal Democrats, and Green Party; and other or none.

Table C.5. Heterogeneity in Information Treatment Effects on Incentivized Beliefs by Participant's Past Experiences

	Own-Mothers' FT Employment				By Median Birth Penalty	
	Yes: when you were < 12	No: when you were < 12	Yes: when you were ≥ 12	No: when you were ≥ 12	≥ | Median Penalty |	< | Median Penalty |
Treatment	-0.06***	-0.05***	-0.05***	-0.06***	-0.07***	-0.05***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Participants	339	708	494	547	261	253
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. We estimate separately equation (3) on the participant's posterior beliefs about the share of children having an abnormal level of behavioral problems in families where the mother works full-time, for each participant's past experience, *i.e.*, if they had a full-time working mother when aged < 12, if they did not, etc., and we display here $\hat{\gamma}$ associated with D_i for each of these regressions.

Table C.6. Causal forest: heterogeneity in the CATES by individual characteristics

	(1) High Predicted CATE	(2) Low Predicted CATE	(3) Diff.	(4) p-value
FT working mother when age < 12	0.326	0.322	0.004	0.897
FT working mother when age ≥ 12	0.474	0.475	-0.001	0.971
High motherhood penalty	0.532	0.482	0.050	0.256
Age	38.472	38.456	0.015	0.973
Age^2	1532.521	1528.407	4.114	0.908
Woman	0.509	0.485	0.025	0.424
White	0.773	0.818	-0.045	0.067
Born in the UK	0.814	0.835	-0.021	0.374
University graduate	0.644	0.667	-0.023	0.438
FT employment	0.604	0.640	-0.036	0.228
ln(Household income)	8.235	8.277	-0.042	0.092
Number of children	1.716	1.847	-0.131	0.015
Vote: conservative	0.189	0.178	0.011	0.634
Vote: other or none	0.188	0.159	0.028	0.223
Median CATEs	-0.053			
Observations	528	528	1,056	

Notes: We report summary statistics as the mean for each participants' characteristic split by those above or below the median of the conditional average treatment effect (CATEs) estimated via a Causal Forest. We also report the difference between the means in column (3) and p-values in column (4).

C.2 Policy Support

Table C.7. Heterogeneity in Information Treatment Effects on Policy Support by Participant's Characteristics

	Median Age		Gender		Ethnicity		Born in the UK		University Degree		Working Hours		Participant's Income		Number of Children		Vote at last UK General Election		
	≥ 38	< 38	Female	Male	White	Non-white	Yes	No	Yes	No	FT	PT or none	$\geq$ Median	$<$ Median	< 2	≥ 2	Conservative	Liberal	Other or None
Panel A: Subsidized childcare policies																			
Treatment	-0.00	-0.00	0.01	-0.02	-0.02	0.04	0.00	-0.02	0.01	-0.03	-0.02	0.02	-0.01	0.04	-0.02	0.01	-0.00	0.01	-0.06
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.06)	(0.03)	(0.06)	(0.03)	(0.04)	(0.03)	(0.04)	(0.05)	(0.05)	(0.03)	(0.04)	(0.06)	(0.03)	(0.07)
Panel B: Paternity leave policies																			
Treatment	0.03	0.05	0.08*	0.01	0.03	0.09	0.03	0.09	0.05	0.02	0.02	0.09*	0.06	0.10*	0.03	0.04	0.08	0.04	-0.03
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.06)	(0.03)	(0.07)	(0.03)	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.07)	(0.04)	(0.07)
Participants	563	493	525	525	840	216	871	185	692	364	657	399 261	253	613	443				
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. We estimate separately equation 3 on two collected outcomes for policy support in distinct panel, and for each participant's characteristic, *i.e.*, for when the participant is a man, a woman, has a degree, etc. We display here $\hat{\gamma}$ associated with D_i for each of these regressions. For panels A and B respectively, we construct binary variables set to one, indicating a strong level of agreement to subsidized childcare policies and paternity leave policies. We define strong by being above the median response as defined in the pre-registration. Individuals controls follow our previously defined set. Estimates for other genders than male and female not displayed due to sample size issues. For the columns "Vote at last UK General Elections", we asked participants: "Which party did you choose as your primary vote in the last UK General Election?" and provided them with a list of candidate parties. We condensed information into three categories as follows: Conservative Party and Reform UK; Labour, Liberal Democrats, and Green Party; and other or none.

Table C.8. Heterogeneity in Information Treatment Effects on Policy Support by Participant's Past Experiences

	Own-Mothers' FT Employment				By Median Birth Penalty	
	Yes: when you were < 12	No: when you were < 12	Yes: when you were ≥ 12	No: when you were ≥ 12	≥ | Median Penalty |	< | Median Penalty |
Panel A: Subsidized childcare policies						
Treatment	0.05	-0.02	0.03	-0.02	-0.01	0.04
	(0.04)	(0.03)	(0.04)	(0.03)	(0.05)	(0.05)
Panel B: Paternity leave policies						
Treatment	0.09*	0.03	0.08*	0.02	0.06	0.10*
	(0.05)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
Participants	339	708	494	547	261	253
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. We estimate separately equation (3) on two outcomes for policy support, and for each participant's past experience, *i.e.*, if they had a full-time working mother when aged < 12, if they did not, etc., and we display here $\hat{\gamma}$ associated with D_i for each of these regressions. Specifically, panel A displays results for a strong level of agreement with subsidized childcare policies, while panel B displays results for a strong level of agreement with paternity leave policies. We define strong by being above the median response as defined in the pre-registration. Individuals controls follow our previously defined set.

Table C.9. Follow-Up — Associations Between Elicited Beliefs and Policy Support

	(1) Free Childcare Hours			(2) Childcare Policies			(3) Nursery Policies		
θ^{graduate}	-0.017		-0.082	0.000		-0.002	0.000		-0.001
	(0.046)		(0.059)	(0.002)		(0.003)	(0.002)		(0.003)
θ^{rank}		0.074	0.129**		0.004	0.005		0.001	0.002
		(0.052)	(0.064)		(0.003)	(0.003)		(0.003)	(0.003)
Participants	445	445	445	445	445	445	445	445	445
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. This table presents OLS results for the control group (main survey) and for three outcomes collected during the follow-up survey: (1) a continuous measure for the number of hours of free childcare participants think parents should receive, (2) a binary indicator for a strong level of agreement (above the median) to expanding free childcare for parents earning less than £60,000, and (3) a binary indicator for a strong level of agreement to increasing childcare supply through the conversion of existing primary schools into 'school-based' nurseries. Robust standard errors in parentheses. Individuals controls follow our previously defined set.

Table C.10. Follow Up — Information Treatment Effects on Policy Support

	(1) All Participants	(2) By GCSE Beliefs		(3) By θ^{graduate}		(4) By θ^{rank}	
		Under-	Over-	<0	≥ 0	<0	≥ 0
Panel A: Free childcare hours							
Treatment	0.539	0.880	-0.491	0.286	0.730	0.861	0.268
	(0.681)	(0.788)	(1.377)	(0.979)	(0.939)	(1.063)	(0.888)
Difference: *p*-value		0.381		0.741		0.666	
Mean Dep. Var	30.015	29.921	30.292	29.827	30.178	29.820	30.168
Panel B: Childcare policies							
Treatment	-0.021	-0.040	0.035	-0.025	-0.020	-0.012	-0.030
	(0.033)	(0.038)	(0.066)	(0.048)	(0.045)	(0.050)	(0.043)
Difference: *p*-value		0.320		0.945		0.784	
Mean Dep. Var	0.548	0.538	0.575	0.516	0.575	0.518	0.571
Panel C: Nursery policies							
Treatment	-0.028	-0.059*	0.045	-0.003	-0.046	0.016	-0.062
	(0.031)	(0.035)	(0.061)	(0.046)	(0.042)	(0.046)	(0.041)
Difference: *p*-value		0.131		0.482		0.208	
Mean Dep. Var	0.699	0.711	0.664	0.696	0.701	0.711	0.689
Participants	893	667	226	415	478	394	499
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p<0.10$; ** $p<0.05$, *** $p<0.01$. Robust standard errors in parentheses. This table presents OLS results of equation (3) for three outcomes presented in separate panels. Panel A presents results for a continuous measure of the number of hours of free childcare participants think parents should receive, while panels B and C present results for separate binary variables set to one if the participant indicated a strong level of agreement to expanding free childcare for parents earning less than £60,000 (panel B), and a strong level of agreement to increasing childcare supply through the conversion of existing primary schools into 'school-based' nurseries (panel C). All specifications include controls for the pre-registered set of participants' characteristics.

Table C.11. Follow-Up — Heterogeneity in Information Treatment Effects on Policy Support by Participant's Characteristics

	Median Age		Gender		Ethnicity		Born in the UK		University Degree		Working Hours		Participant's Income		Number of Children		Vote at last UK General Election		
	≥ 38	< 38	Female	Male	White	Non-white	Yes	No	Yes	No	FT	PT or none	≥ Median	< Median	< 2	≥ 2	Conservative	Liberal	Other or None
Panel A: Free childcare hours																			
Treatment	-0.48	1.56*	1.72**	-0.47	0.14	2.31	0.01	3.53**	1.65**	-1.31	0.03	1.55	1.73	1.83	0.05	1.12	-1.68	0.83	1.58
	(0.97)	(0.95)	(0.87)	(1.03)	(0.74)	(1.62)	(0.74)	(1.65)	(0.83)	(1.17)	(0.86)	(1.12)	(1.29)	(1.25)	(0.87)	(1.09)	(1.61)	(0.81)	(1.87)
Panel B: Childcare policies																			
Treatment	-0.04	0.00	0.03	-0.06	-0.03	0.02	-0.04	0.08	0.01	-0.07	-0.05	0.03	0.04	0.01	0.00	-0.05	0.07	-0.03	-0.13
	(0.05)	(0.05)	(0.05)	(0.05)	(0.04)	(0.07)	(0.04)	(0.08)	(0.04)	(0.05)	(0.04)	(0.05)	(0.07)	(0.07)	(0.04)	(0.05)	(0.07)	(0.04)	(0.08)
Panel C: Nursery policies																			
Treatment	-0.06	0.01	-0.06	0.01	-0.04	0.04	-0.03	-0.01	0.01	-0.09*	0.00	-0.07	-0.09	-0.06	-0.06	0.01	-0.09	-0.02	0.00
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.07)	(0.03)	(0.08)	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.06)	(0.04)	(0.05)	(0.07)	(0.04)	(0.08)
Participants	480	413	436	452	703	190	733	160	589	304	561	332 213	213	516	377				
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. We estimate separately equation 3 on three collected outcomes from the follow-up for policy support in distinct panel, and for each participant's characteristic, *i.e.*, for when the participant is a man, a woman, has a degree, etc. We display here $\hat{\gamma}$ associated with D_i for each of these regressions. Panel A presents results for a continuous measure of the number of hours of free childcare participants think parents should receive, while panels B and C present results for separate binary variables set to one if the participant indicated a strong level of agreement to expanding free childcare for parents earnings less than £60,000 (panel B), and to increasing childcare supply through the conversion of existing primary schools into 'school-based' nurseries (panel C). Individuals controls follow our previously defined set. Estimates for other genders than male and female not displayed due to sample size issues. For the columns "Vote at last UK General Elections", we asked participants: "Which party did you choose as your primary vote in the last UK General Election?" and provided them with a list of candidate parties. We condensed information into three categories as follows: Conservative Party and Reform UK; Labour, Liberal Democrats, and Green Party; and other or none.

Table C.12. Follow-Up — Heterogeneity in Information Treatment Effects on Policy Support by Participant's Past Experiences

	Own-Mothers' FT Employment				By Median Birth Penalty	
	Yes: when you were $<$ 12	No: when you were $<$ 12	Yes: when you were $\geq$ 12	No: when you were $\geq$ 12	$\geq$ | Median Penalty |	$<$ | Median Penalty |
Panel A: Free childcare hours						
Treatment	1.35	0.23	1.17	0.23	1.73	1.83
	(1.35)	(0.80)	(1.03)	(0.93)	(1.29)	(1.25)
Panel B: Childcare policies						
Treatment	-0.07	0.00	-0.01	-0.02	0.04	0.01
	(0.06)	(0.04)	(0.05)	(0.05)	(0.07)	(0.07)
Panel C: Nursery policies						
Treatment	-0.04	-0.02	-0.09**	0.04	-0.09	-0.06
	(0.06)	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)
Participants	279	607	410	470	213	213
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes

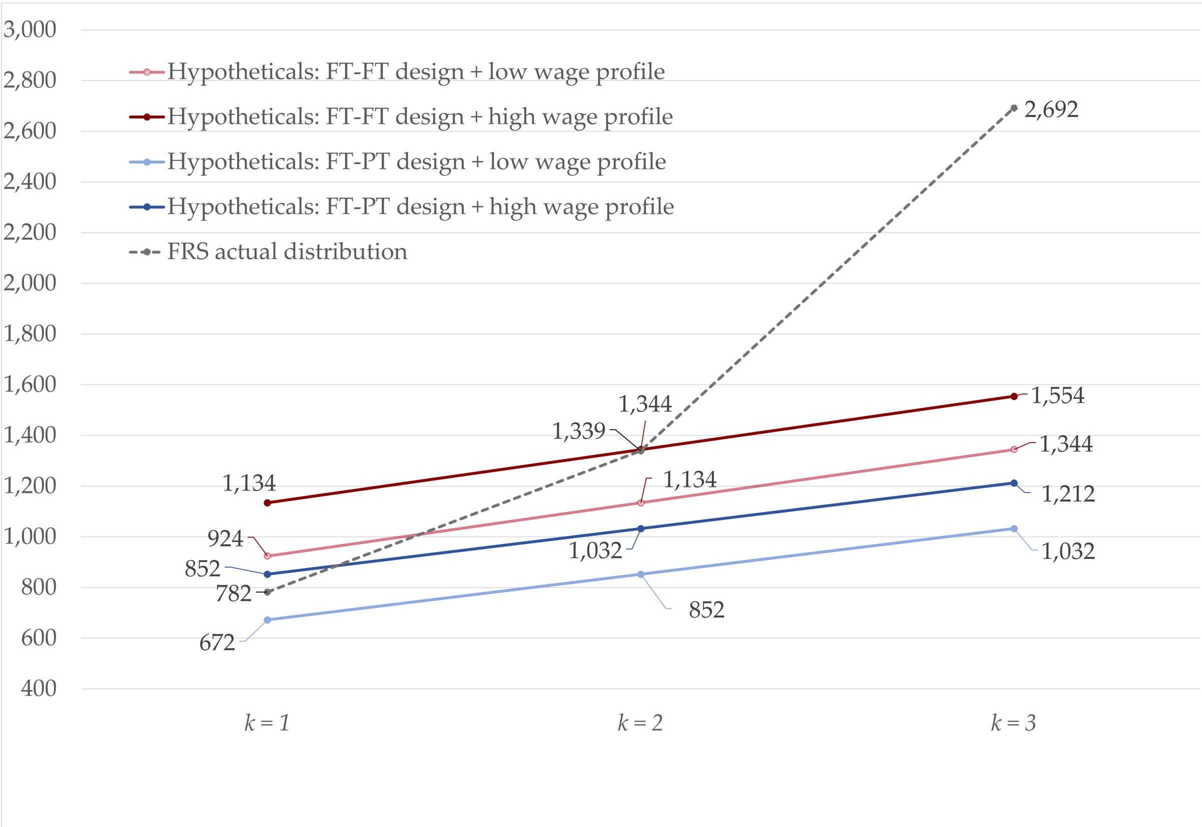
Notes: * p <0.10; ** p <0.05, *** p <0.01. Robust standard errors in parentheses. We estimate separately equation (3) on three outcomes for policy support from the follow-up survey, and for each participant's past experience, *i.e.*, if they had a full-time working mother when aged < 12, if they did not, etc., and we display here $\hat{y}$ associated with D_i for each of these regressions. Specifically, for panels A and B, we construct binary variables set to one, indicating a strong level of agreement to subsidized childcare policies and paternity leave policies. We define strong by being above the median response as defined in the pre-registration. For panel C, we use the continuous gender norms score where higher values imply more liberal views toward the role of mothers. Individuals controls follow our previously defined set.

D Survey Technical Details and Questionnaires

D.1 Survey Technical Details

D.1.1 Beliefs Elicitation Survey

Figure D.1. Weekly Household Labor Income Distribution (£)



Notes: This table presents the distribution of weekly household labor income across the hypothetical wage profiles introduced in Table 1, contrasted with tertiles of the weekly household income distribution (dashed-line), drawn from the Family and Resources Survey 2022-2023.

D.1.2 Information Treatment Construction

We present below details on how we build the information treatment *i.e.*, the share of children passing five or more GCSEs with a grade C/4 or higher, as well as the share of children having an abnormal level of behavioral problems. For both metrics, we use the Millennium Cohort Study (MCS) also described below.

The Millennium Cohort Study. The Millennium Cohort Study (MCS) follows the lives of around 19,000 young people ($N = 18,818$) born across England, Scotland, Wales and Northern Ireland in 2000-02. The MCS offers a wide range of measures tracking the cohort members' physical, socio-emotional, cognitive, and behavioral development over time, along with detailed insights into their daily lives, behaviors, and experiences. Additionally, it provides comprehensive data on economic conditions, parenting practices, relationships, and family life, as reported by both resident parents. [35] For our analysis, we use the parents' reported data on various factors, such as their education levels, employment statuses, and weekly working hours, as well as the joint net household income. We then combine this data with relevant information about their child(ren), specifically focusing on non-cognitive outcomes and later GCSE pass rates.

Data management. We construct two different datasets, respectively, for the two metrics we want to construct: (i) the share of children having an abnormal level of behavioral problems, and (ii) the share of children passing five or more GCSEs with a grade C/4 or higher. This leads us to work with different waves of MCS. For the first metrics (i), we make use of sweeps 1 (9 months of the child), 3 (age 5), and 4 (age 7). Specifically, we use sweep 1 to get information on parents' highest educational achievement. The final education variable we consider is a 3-category variable (High, Medium and Low), as presented in Table D.1 below. We extract the mother's working hours from sweeps 3 and 4 (ages 5 and 7) corresponding to the child's primary school age, and use sweep 4 to get infomation on parental income.[36] This wave also corresponds to the time of the SDQ measurement (see next paragraph for more details). Thus, we merge information reported from sweeps 1, 3 and 4, keeping England only, as well as dual-parents families.[37] This leaves us with a sample of $N = 6,787$ children. For the second metrics *i.e.*, the information treatment (ii), we make use of the same waves as above but also include sweeps 7 (age 17), when the GCSEs outcomes are measured. In turn, we merge parents' reported information from sweeps 1, 3, 4 and 7. Keeping only England, as well as dual-parents families, we end up with a sample of $N = 5,457$ children.

Metrics. The two metrics have been constructed at the individual (child) level. First, to obtain the share of children having an abnormal level of behavioral problems, we mainly use wave 4 (age 7) in which parents respond to the Strengths and Difficulties Questionnaire (SDQ). Specifically, we focus on the externalizing (behavior) score — ranging from 0 to 20 — corresponding to the sum of the conduct and hyperactivity scales.[38] We calculate this score for each child aged 7, and further create a dummy variable equal to 1 if this score is equal or greater than 11. Indeed, children with scores between 11 and

[35] See the MCS website for a more detailed description of the survey.
[36] The income variable provided by MCS is a 19-category variable, ranging from less than £1,600 a year, to £100,000 or more.
[37] We do not consider the second wave (age 3 of the child) because it does not correspond to the primary school age.
[38] See the Early Intervention Foundation website.

Table D.1. Education Coding Scheme

3-category coding	9-category coding	Questionnaire items included
High education	1. Higher degree	Higher degree (A)
	2. Bachelor's degree	First degree (A) Professional qualifications at degree level (V)
	3. HE below degree	Diplomas in higher education (A) Nursing or other medical qualifications (V)
Medium education	4. A-level	A/AS/S level (A) NVQ/SVQ/GSVQ Level 3 (V)
	5. Trade apprenticeship	Trade apprenticeship (V)
	6. GCSE A-C	O-level/GCSE grades A-C (A) NVQ/SVQ/GSVQ Level 2 (V)
Low education	7. GCSE D-G	GCSE grades D-G (A) NVQ/SVQ/GSVQ Level 1 (V)
	9. None	None of these (A & V)

Notes: We excluded category 8, corresponding to "other qualification including oversea" for consistency purposes. (A) stands for academic, (V) for vocational.

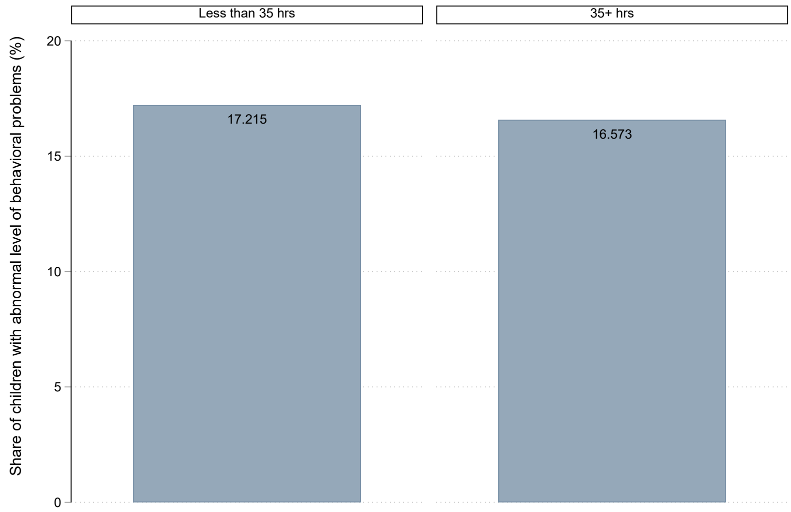
20 are considered as having an "abnormal" level of behavioral problems.[39] Second, to obtain the share of 5 or more GCSEs passed with a grade of C/4 or higher, we use the wave 7 (age 17) in which pupils are asked about their educational attainment.[40] Since the exam conditions and requirements vary in the United Kingdom, we restrict our analysis to England only where students are expected to take nine GCSEs subjects, among which 3 of them are compulsory — Maths, English and Science.[41] Thus, we calculate the within-person number of GCSEs passed and create a dummy variable set to 1 if they have achieved 5 or more GCSEs with grades ranging from A* to C(4).

Estimation. To derive both final metrics, we proceed in three steps, separately for each metric. First, we estimate a probit model where the dependent variable is a dummy set to 1 if the mother worked part-time or less during primary school years of the child, and the independent variables are categorical variables for the mother's and father's education, as well as income categories. Second, we generate predicted values from the probit model and convert them to probabilities using a normal cumulative distribution function. These give the probability that the mother works part-time based on the observed variables (education and income). Third, we create weights to adjust for the likelihood of being part-time based on those observed characteristics. Thus, we provide the average for both metrics in Figure D.2 for when the mother worked part-time or less during the child's primary school age, and the re-weighted average for when the mother worked full-time.

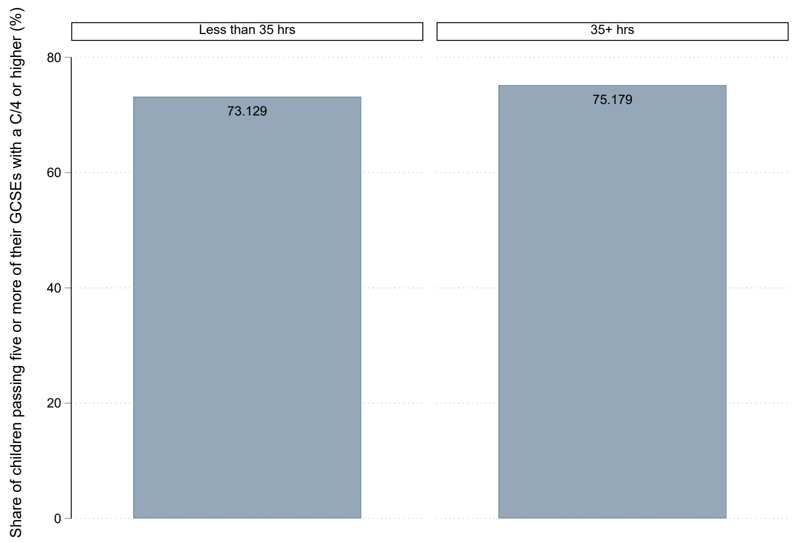
[39] This threshold for the abnormal level of behavioral problems is provided by the official SDQ website.
[40] At the age of 17, we expect pupils to have taken their GCSEs.
[41] See this website for a full description of GCSE requirements.

Figure D.2. Distribution of Constructed Metrics

(a) Behavioral Problems



(b) GCSE Pass Rates



D.1.3 Motherhood Penalty

In order to produce the heterogeneity results by participant's past experiences, we present below how we construct an indicator for women above the median motherhood penalty (*e.g.*, Kleven et al., 2019).

Information collection. At the end of the survey, after collecting the demographic information, we ask information about the personal employment history of the participant from age 16 up to their current age. This enables us to construct a yearly panel of participants, with updated information (from years 1972 to 2024) on whether they were (i) in education, (ii) employed full-time, (iii) employed part-time (iv) unemployed, (v) retired, (vi) stay-at-home parent, or (vii) in any other type of activity. Specifically, participants are shown a table, presented in Figure D.24 in the Appendix.

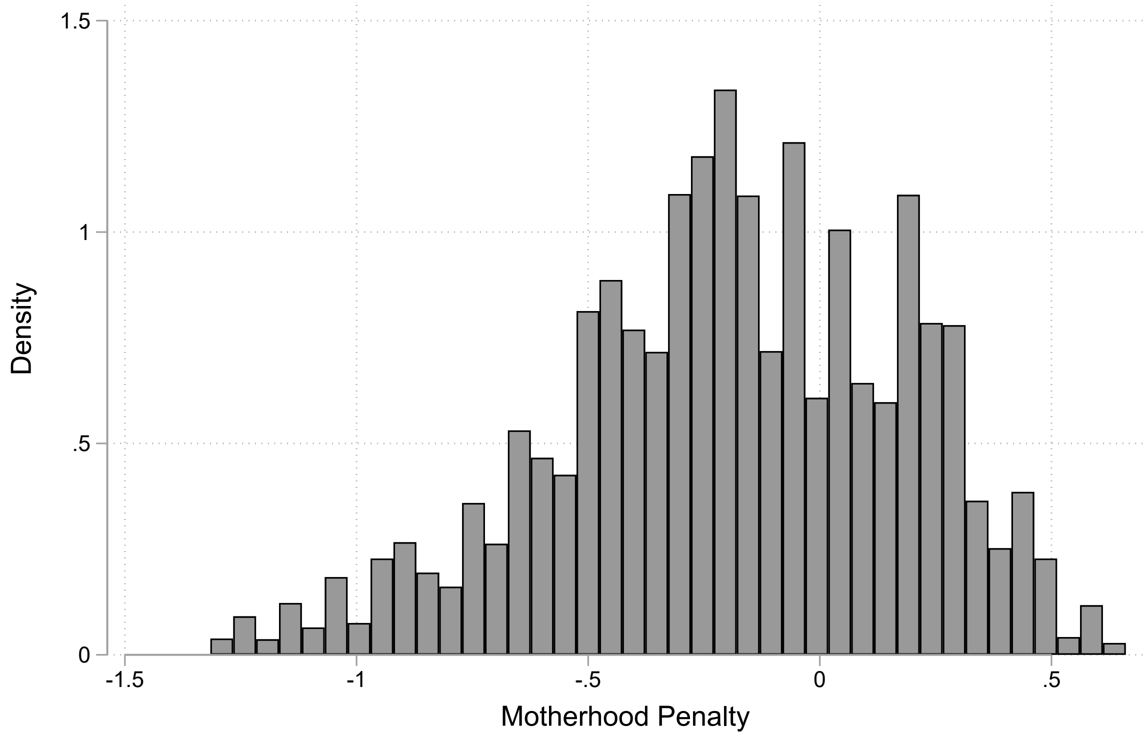
Sample. We keep participants who experienced the first childbirth during the standard reproductive period, between the ages of 18 and 45. We end up with a sample of N= $1,025$ participants, and $23,951$ observations.

Indicator construction. Our aim is to construct a binary indicator flagging women who experienced a motherhood employment penalty above the median of the sample.[42] To do so, we calculate each woman's motherhood employment penalty — the impact of motherhood on the likelihood of being employed with respect to men controlling for age and time effects —, and further create a binary indicator for women whose penalty is above the sample median ($\approx -19\%$). We present below in Figure D.3 a histogram of their calculated penalties.

Event study analyses. We also conduct the event-study methodology proposed by Kleven et al. (2019), and present below, in Figure D.4, a graphical representation of these regressions, for men and women, which aligns with previous results from the literature (*e.g.*, Kleven et al., 2021; Kleven et al., 2023). Indeed, men's likelihood of being employed does not seem to be affected by the first childbirth, while women's employment likelihood in the 10 years after the first childbirth reduces by a significant margin of $\approx 29\%$ with respect to men.

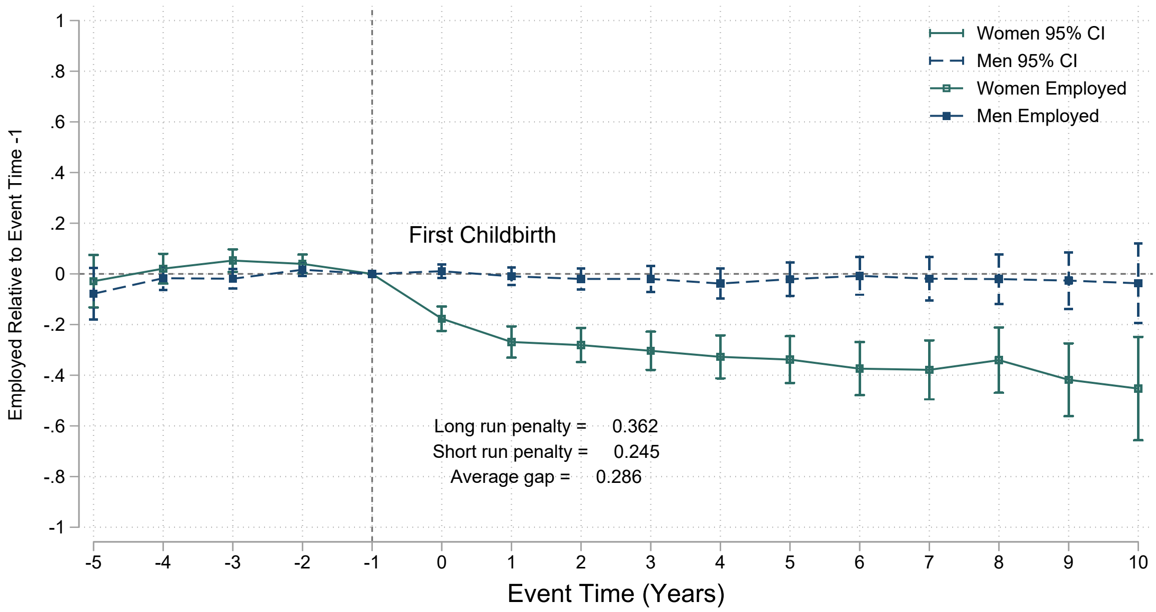
[42]Given that men are unaffected by parenthood (see Figure D.4), we focus on women only.

Figure D.3. Distribution of Motherhood Penalties



Notes: This figure presents an histogram of women's motherhood penalties, *i.e.*, the impact of motherhood on the likelihood of being employed with respect to men.

Figure D.4. Impact of Parenthood on Employment

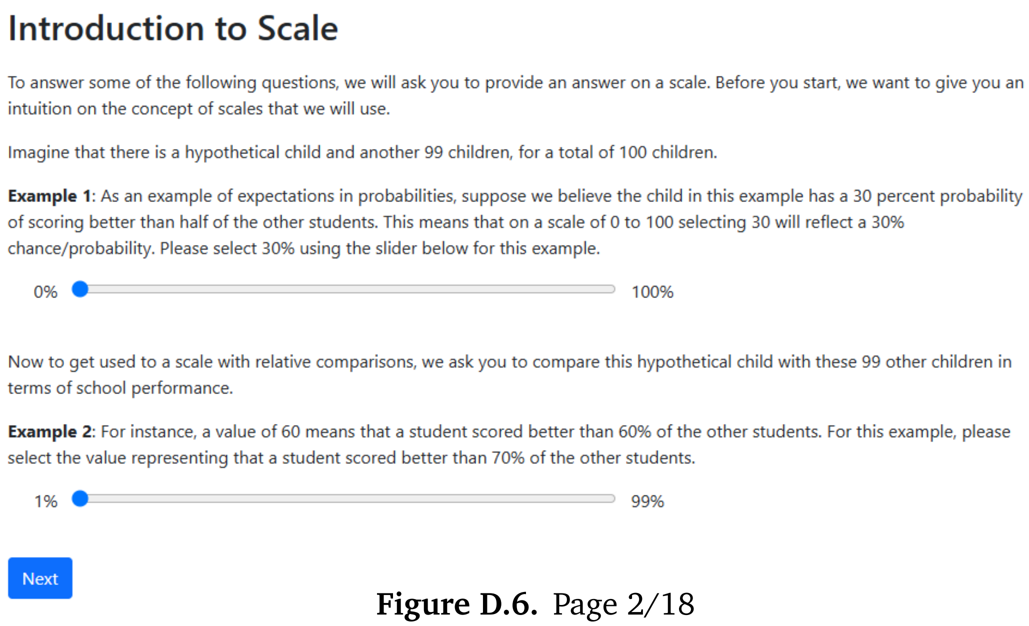


Notes This figure presents the impact of having a child on a binary variable set to one for being employed at time t, by gender. It further indicates the percentage by which women are falling behind men (1) in the long-run ('long run penalty'), *i.e.*, between seven and ten years post-parenthood, (2) in the short-run ('short run penalty'), *i.e.*, in three years after the first childbirth, and (3) on average ('average gap'), *i.e.*, in the ten years following parenthood.

D.2 Survey Screenshots and Questionnaires

D.2.1 Main Survey

Figure D.5. Page 1/18



Introduction to Scale

To answer some of the following questions, we will ask you to provide an answer on a scale. Before you start, we want to give you an intuition on the concept of scales that we will use.

Imagine that there is a hypothetical child and another 99 children, for a total of 100 children.

Example 1: As an example of expectations in probabilities, suppose we believe the child in this example has a 30 percent probability of scoring better than half of the other students. This means that on a scale of 0 to 100 selecting 30 will reflect a 30% chance/probability. Please select 30% using the slider below for this example.

0% 100%

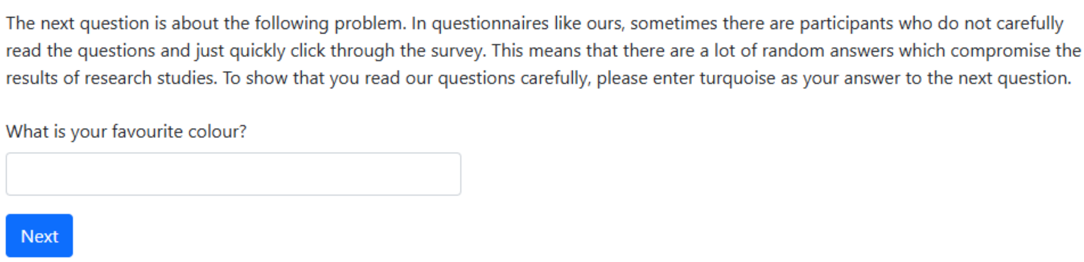
Now to get used to a scale with relative comparisons, we ask you to compare this hypothetical child with these 99 other children in terms of school performance.

Example 2: For instance, a value of 60 means that a student scored better than 60% of the other students. For this example, please select the value representing that a student scored better than 70% of the other students.

1% 99%

Next

Figure D.6. Page 2/18



The next question is about the following problem. In questionnaires like ours, sometimes there are participants who do not carefully read the questions and just quickly click through the survey. This means that there are a lot of random answers which compromise the results of research studies. To show that you read our questions carefully, please enter turquoise as your answer to the next question.

What is your favourite colour?

Next

Notes: This figure shows the “turquoise” screener.

Figure D.7. Page 3/18

We are interested in your beliefs about children's future outcomes, comparing families with different financial resources and time demands.

▼ **Setup:**

Please imagine an average family in your community. Suppose this family consists of a father and a mother who are both employed, and they have a **boy** who is aged **4**. Suppose household expenditure decisions are made jointly by the father and the mother, and this hypothetical family spends **10%** of their total income on the child's educational and extracurricular activities such as clubs, tutoring, music, sports, etc.

We will show you different scenarios, and ask your opinion about the likelihood that the child will be successful in education and the labour market. There are no clear right or wrong answers, and we know these questions are difficult. Please try to consider each scenario carefully and tell us what you believe the likely outcomes will be.

Scenario 1: The **father** works **42** hours per week at a wage of **£17** per hour.
The **mother** works **35** hours per week at a wage of **£12** per hour.

- What do you think is the probability that this child will eventually graduate from university?

0% 100%

- When the child is 30 years old, how do you think this child's earnings will compare to other 30 years old?

1% 99%

Scenario 2: The **father** works **42** hours per week at a wage of **£12** per hour.
The **mother** works **35** hours per week at a wage of **£12** per hour.

- What do you think is the probability that this child will eventually graduate from university?

0% 100%

- When the child is 30 years old, how do you think this child's earnings will compare to other 30 years old?

1% 99%

Scenario 3: The **father** works **42** hours per week at a wage of **£22** per hour.
The **mother** works **35** hours per week at a wage of **£12** per hour.

- What do you think is the probability that this child will eventually graduate from university?

0% 100%

- When the child is 30 years old, how do you think this child's earnings will compare to other 30 years old?

1% 99%

Next

Notes: Bolded words correspond to our randomized survey features.

Figure D.8. Page 4/18

We are interested in your opinion on children's future outcomes, comparing families with different financial resources and time demands.

▸ **Setup:**

Scenario 4: The **father** works **35** hours per week at a wage of **£12** per hour.
The **mother** works **42** hours per week at a wage of **£17** per hour.

- What do you think is the probability that this child will eventually graduate from university?

0% 100%

- When the child is 30 years old, how do you think this child's earnings will compare to other 30 years old?

1% 99%

Scenario 5: The **father** works **35** hours per week at a wage of **£12** per hour.
The **mother** works **42** hours per week at a wage of **£12** per hour.

- What do you think is the probability that this child will eventually graduate from university?

0% 100%

- When the child is 30 years old, how do you think this child's earnings will compare to other 30 years old?

1% 99%

Scenario 6: The **father** works **35** hours per week at a wage of **£12** per hour.
The **mother** works **42** hours per week at a wage of **£22** per hour.

- What do you think is the probability that this child will eventually graduate from university?

0% 100%

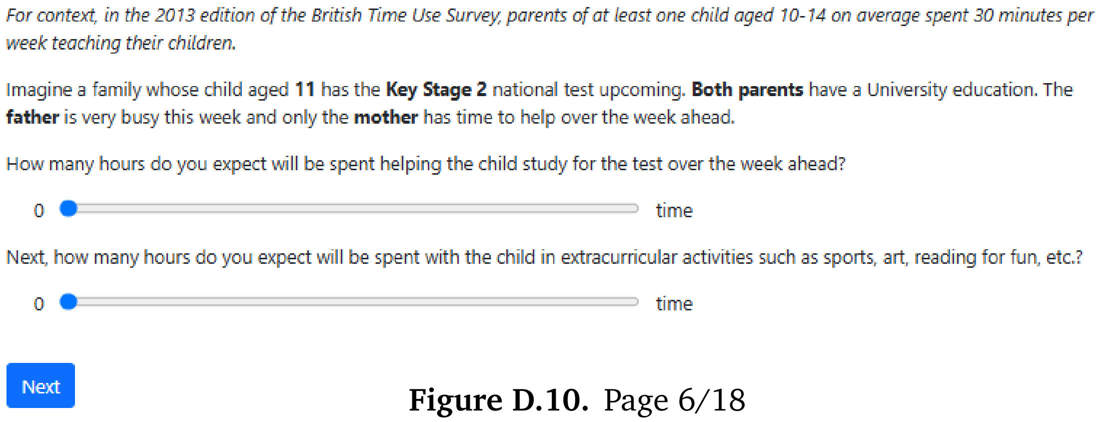
- When the child is 30 years old, how do you think this child's earnings will compare to other 30 years old?

1% 99%

Next

Notes: Bolded words correspond to our randomized survey features.

Figure D.9. Page 5/18



For context, in the 2013 edition of the British Time Use Survey, parents of at least one child aged 10-14 on average spent 30 minutes per week teaching their children.

Imagine a family whose child aged **11** has the **Key Stage 2** national test upcoming. **Both parents** have a University education. The **father** is very busy this week and only the **mother** has time to help over the week ahead.

How many hours do you expect will be spent helping the child study for the test over the week ahead?

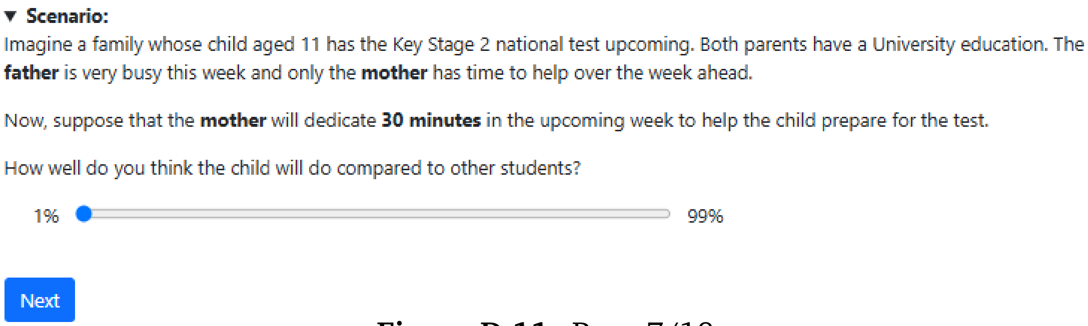
0 time

Next, how many hours do you expect will be spent with the child in extracurricular activities such as sports, art, reading for fun, etc.?

0 time

Next

Figure D.10. Page 6/18



▼ **Scenario:**
Imagine a family whose child aged 11 has the Key Stage 2 national test upcoming. Both parents have a University education. The **father** is very busy this week and only the **mother** has time to help over the week ahead.

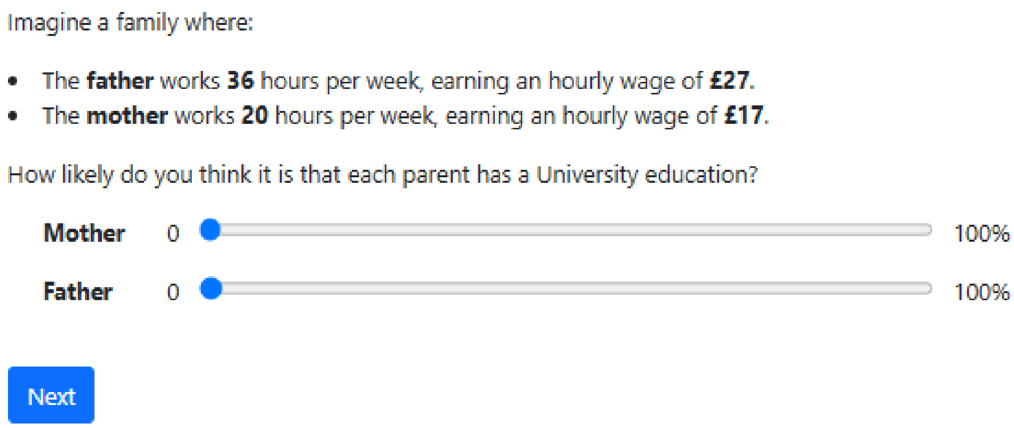
Now, suppose that the **mother** will dedicate **30 minutes** in the upcoming week to help the child prepare for the test.

How well do you think the child will do compared to other students?

1% 99%

Next

Figure D.11. Page 7/18



Imagine a family where:

- The **father** works **36** hours per week, earning an hourly wage of **£27**.
- The **mother** works **20** hours per week, earning an hourly wage of **£17**.

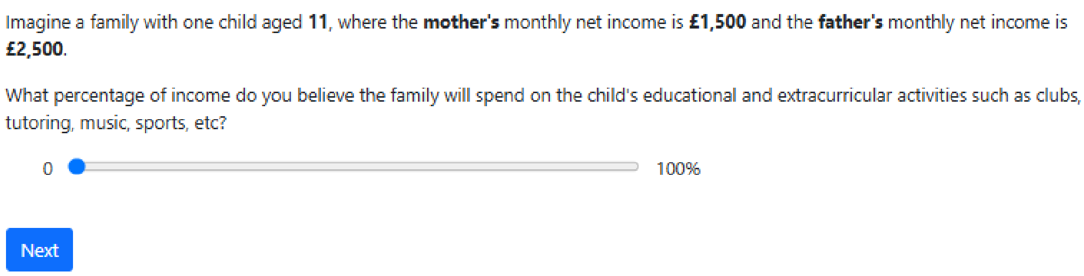
How likely do you think it is that each parent has a University education?

Mother 0 100%

Father 0 100%

Next

Figure D.12. Page 8/18



Imagine a family with one child aged **11**, where the **mother's** monthly net income is **£1,500** and the **father's** monthly net income is **£2,500**.

What percentage of income do you believe the family will spend on the child's educational and extracurricular activities such as clubs, tutoring, music, sports, etc?

0 100%

Next

Figure D.13. Page 9/18

How sure are you about your answers to the previous questions under the hypothetical setting?

- Very sure
- Sure
- Somewhat sure
- Unsure
- Very unsure

Next

Figure D.14. Page 10/18

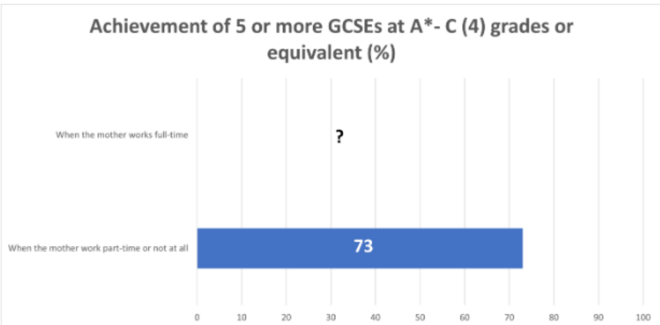
We, as researchers at the University of Strathclyde, have calculated the share of children passing five or more GCSEs with a grade of C/4 or higher.

Among families where the mother worked part-time or not at all, around **73%** of children passed five or more GCSEs with a C/4 or higher. This information is also shown visually in the graph below.

We then computed this statistic for families with similar income and education levels but where the mother worked full-time (35 hours or more). In these families, what percentage of children do you believe eventually passed five or more GCSEs with a C/4 or higher?

You will gain £1.50 if your answer is within 2 percentage points of the true number.

0% 100%



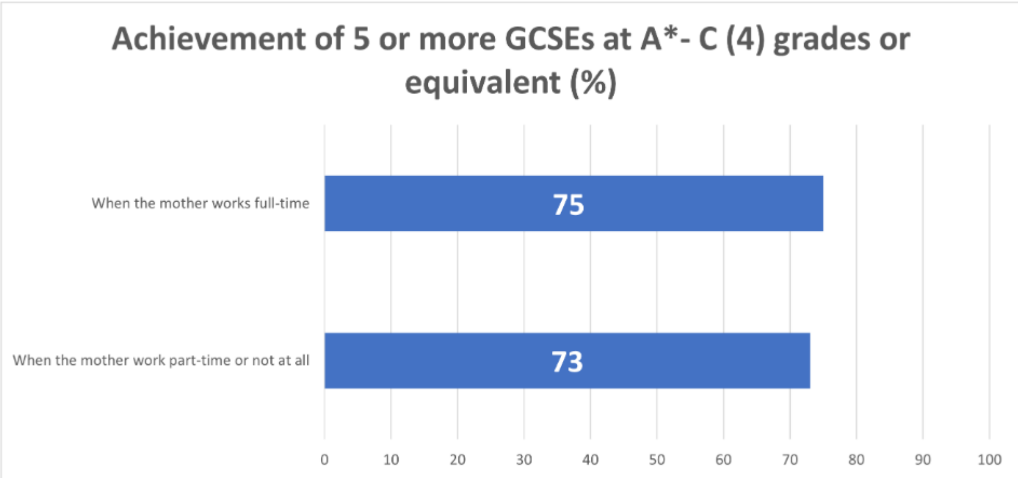
Note: Authors' calculations using the Millennium Cohort Study, a nationally representative sample of families and children born in the year 2000. Mother's working hours correspond to the average number of weekly hours worked, when the child was aged between 5 and 7. Families with mothers working full-time (35 hours or more) are adjusted to have similar income and education as families with mothers working less.

Next

Figure D.15. Page 11/18

For mother worked full-time (35 hours or more), adjusted to have similar education and income levels as mothers working fewer than 35 hours, we found that around **75%** of their children eventually passed five or more GCSE's with a C/4 or higher.

This means these children did about **2 percentage points better** compared to those of mothers working less than 35 hours per week.



Next

Figure D.16. Page 12/18

Research shows that after having children, women experience a drop in labour earnings. This is often explained by the fact that, due to childcare responsibilities, they sort into jobs that offer lower wages but are more flexible and do not require long hours. We are interested in your opinion on two questions about government policy.

Do you think that the government should offer...

- ... policies such as subsidized childcare and universal childcare to help women with children work longer hours?

○ Strongly disagree ○ Disagree ○ Neither agree or disagree ○ Agree ○ Strongly agree

- ... policies such as paternity leave to help women with children return sooner to work after the childbirth?

○ Strongly disagree ○ Disagree ○ Neither agree or disagree ○ Agree ○ Strongly agree

Next

Figure D.17. Page 13/18

The data that we used to calculate the share of children passing five or more GCSEs also provides information on the children's externalising behavioural problems at age 7 (*e.g.,* conduct problems and hyperactivity/inattention).

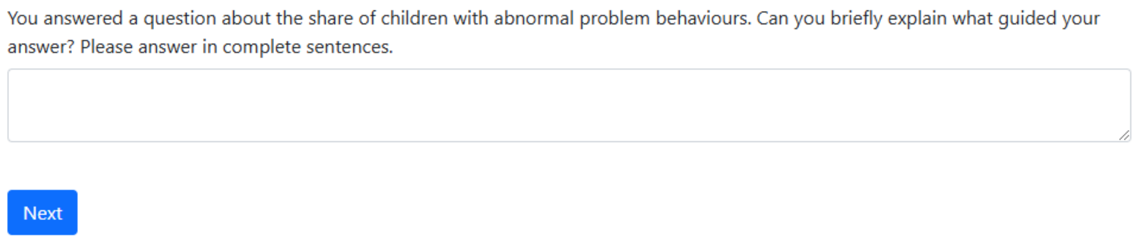
Among families where the mother worked part-time or not at all, **out of 100 children** aged 7, we found that **around 17** had an abnormal level of behavioural problems.

We then computed this statistic for families with similar income and education levels but where the mother worked full-time (35 hours or more). In this group, **out of 100 children**, how many do you believe had an abnormal level of behavioural problems?

You will gain £1.50 if your answer is within 2 points of the true number.

Next

Figure D.18. Page 14/18

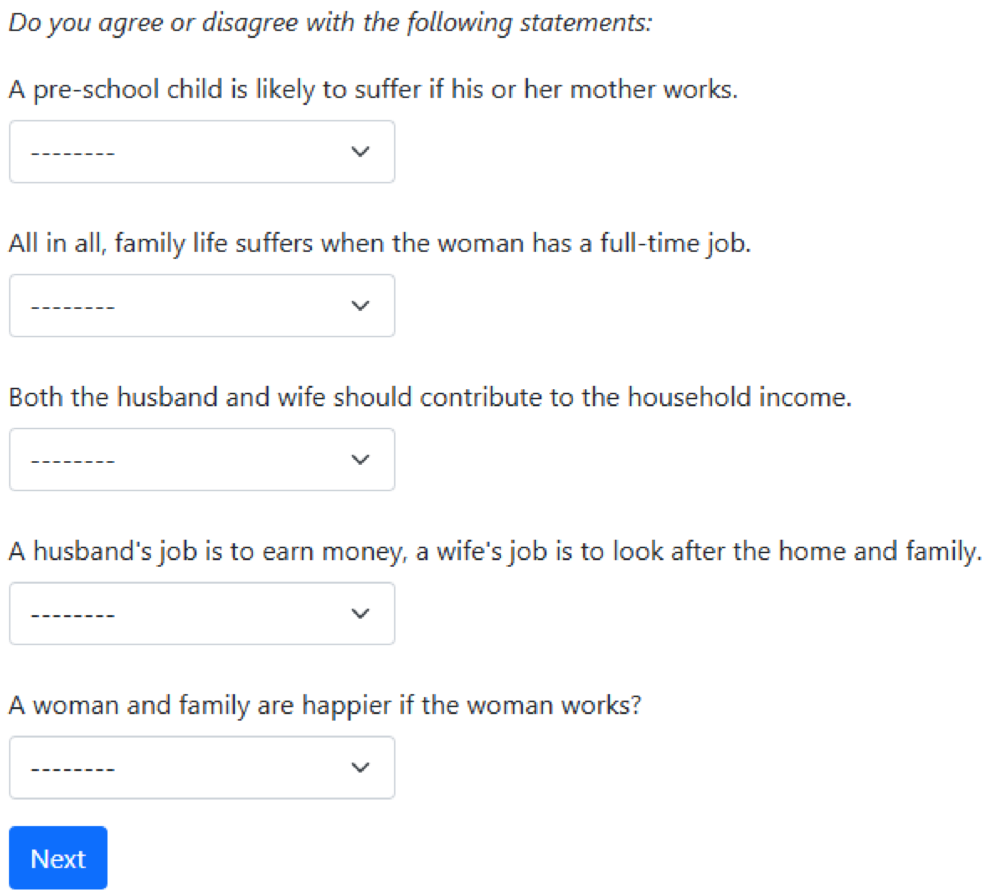


You answered a question about the share of children with abnormal problem behaviours. Can you briefly explain what guided your answer? Please answer in complete sentences.

Next

Notes: With this open question, we classified participants' answers with two schemes. The first is whether they expect mothers working full-time to cause harm, no harm, or they provide an unclear answer. The second classifies answers into five categories: (1) better resources, (2) lower time investments, (3) no relationship, (4) other, and (5) unclear. We use the first classification to see if information leads respondents to express expectations of less harm from mothers working full-time, and we use the second classification to look at whether information makes respondents less likely to mention the lower time investment model.

Figure D.19. Page 15/18



Do you agree or disagree with the following statements:

A pre-school child is likely to suffer if his or her mother works.

All in all, family life suffers when the woman has a full-time job.

Both the husband and wife should contribute to the household income.

A husband's job is to earn money, a wife's job is to look after the home and family.

A woman and family are happier if the woman works?

Next

Figure D.20. Page 16/18 — Part 1

Next, we are going to ask some questions about yourself.

What is your age?

What is your gender?

- Male
- Female
- Other
- Prefer not to say

To which of these ethnic groups do you consider you belong?

- Asian or Asian British
- Black, Black British, Caribbean or African
- Mixed or multiple ethnic groups
- White
- Other ethnic group

Are you born in the UK?

- Yes
- No
- Prefer not to say

Which is the highest qualification you have?

- No Qualification
- Other Qualification
- GCSE or equivalent
- A-levels or equivalent
- Degree or Higher

Figure D.21. Page 16/18 — Part 2

Which party did you choose as your primary vote in the last UK General Election?

- ◯ Conservative
- ◯ Labour
- ◯ Liberal Democrat
- ◯ Green Party
- ◯ Reform UK
- ◯ Other
- ◯ None

Which of this best describes your current employment situation?

- ◯ Self-employed
- ◯ Employed
- ◯ Unemployed
- ◯ Retired
- ◯ On maternity leave
- ◯ Family care or home
- ◯ Full-time student
- ◯ Long-term sick or disabled
- ◯ On apprenticeship
- ◯ Other

What was your (main) job in the week ending last Sunday? Please write your job title below.

Do you work part-time or full-time?

- ◯ Part-time
- ◯ Full-time
- ◯ Not Applicable

How many hours do you typically work per week?

Figure D.22. Page 16/18 — Part 3

What is your personal typical monthly net income?

[-------- ▾]

What is your current marital status?

- ◯ Married
- ◯ Living as couple
- ◯ Widowed
- ◯ Divorced
- ◯ Separated
- ◯ Single, never married
- ◯ Civil partnership
- ◯ Other

What is your partner's gender?

- ◯ Male
- ◯ Female
- ◯ Other
- ◯ Prefer not to say
- ◯ I do not have a partner

Does your partner work part-time or full-time?

- ◯ Part-time
- ◯ Full-time
- ◯ Not Applicable

What is your partner's typical monthly net income?

[-------- ▾]

How many children (aged 0-16) do you have in your family?

[-------- ▾]

Figure D.23. Page 16/18 — Part 4

What is the year of birth of your first (eldest) child (adopted or biological)?

How many hours per week do you spend helping your child(ren) develop their skills (e.g. helping with homework/checking workbooks, reading books/telling stories, playing board or card games, etc)? If you have more than one child, please report the overall number of hours.

How many hours per week do you spend doing outdoors activities with your child(ren) (e.g. going to the playground, taking a walk, bringing your child to any sporting activity, going to museums/galleries, etc)? If you have more than one child, please report the overall number of hours.

Thinking back to when you were...	**was your mother working?**	**was your father working?**
less than 12 years old	-------	-------
between 12 and 18 years old	-------	-------

Figure D.24. Page 16/18 — Part 5

We would now like to ask you for some information about your personal history starting at age 16.

Please fill out the table below as follows:

Please state what has happened in your life since you were 16. It is important that you give some answer for <u>every</u> year of your life up to your current age. If you are over 60, please provide your responses up to age 60. If more than one answer applies in a particular year, please select all answers that apply.

At the age of...	**16**	**17**	**18**	**19**	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**	**28**	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**	**37**	**38**	**39**	**40**	**41**
I was...																										
in education (*e.g.*, GCSEs, A-levels, college, university)	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
employed full-time	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
employed part-time	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
unemployed	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
retired	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
stay-at-home parent	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
other	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○

Next

Figure D.25. Page 17/18

If you had to guess, what was the purpose of this study?

Next

Figure D.26. Page 18/18

Thanks for completing all our questions!

Children's GCSE pass rate results:
Your answer about the share of students passing five or more GCSEs with a C/4 or higher does not fall within the range.

Children's behavioural problems results:
Your answer about the number of children out of 100 having abnormal behavioural problems does not fall within the range.

To be paid, please redirect back to Prolific to confirm your participation: https://app.prolific.com/submissions/complete?cc=C8L708C0. Your total payment is: £2.50.
This consists of your base pay, which is £2.50, plus any bonuses if you won them. Bonus payments will be processed after the base payment.
If you want to keep track of your payment, please keep your completion code.

Contacts & Final Report:
If you have questions or concerns about the study, you can contact the researchers at jonathan.norris@strath.ac.uk and agnese.romiti@strath.ac.uk. Please be aware that you will break the confidentiality protocol. For more information and findings of the project, please visit https://sites.google.com/view/svyresults.

D.2.2 Obfuscated Follow-Up

Figure D.27. Page 1/6

This is a survey about your views regarding some policy stances of the Conservative and Labour parties in the recent general election. We will first collect some basic information about you and then ask for your views about some policy questions.

What is your age?

What is your gender?

- Male
- Female
- Other
- Prefer not to say

Which party did you vote for in the UK General Election?

- Conservative
- Labour
- Liberal Democrat
- Green Party
- Other
- Did not vote

Next

Figure D.28. Page 2/6

Ahead of the election, the Conservative party pledged that they would reinstate mandatory national service (military or non-military) for all 18-year-olds. For the majority of people this would entail 25 days of community volunteering over the year and for a smaller group a full year of military service.

Do you agree with reinstating mandatory national service?

- Strongly agree
- Agree
- Neither agree or disagree
- Disagree
- Strongly disagree

How many months of mandatory national service do you think 18-year-olds should go through?

0 18

Next

Figure D.29. Page 3/6

Before the election, the Labour party promised to introduce a new tax on private schools. The new policy would impose a 20% VAT on private school tuition fees. They claim that this would raise government income by £1.7 billion, which would then be spent to increase the quality of state schools.

Do you agree with increasing taxes on private schools to increase funding for state schools?

- Strongly agree
- Agree
- Neither agree or disagree
- Disagree
- Strongly disagree

What do you think the VAT on private schools should be?

0% | less than 20% | 20% | more than 20%

Next

Figure D.30. Page 4/6

In 2023, the government announced a £4 billion expansion of free childcare which would provide parents earning less than £60,000 with 30 free hours of childcare per week. Before the election, the Labour party promised to back this expansion if they won the election.

Do you agree with the policy to increase the hours of free childcare for 2- to 4-year-olds from 15 to 30 hours?

- Strongly agree
- Agree
- Neither agree or disagree
- Disagree
- Strongly disagree

How many hours of free childcare do you think parents of 2- to 4-year-old children should receive?

0 time

Next

Figure D.31. Page 5/6

In a plan to increase the availability of childcare, the Labour Party pledged, prior to the recent election, to convert existing primary schools into 'school-based' nurseries, at a cost of £40,000 per classroom. The party claims that this initiative will create 3,334 new nurseries in high-need areas that currently lack sufficient childcare places. This policy will be funded by the VAT levied on private schools.

Do you agree with this policy?

- Strongly agree
- Agree
- Neither agree or disagree
- Disagree
- Strongly disagree

Next

Figure D.32. Page 6/6

Thanks for completing all our follow-up questions!

To be paid, please redirect back to Prolific to confirm your participation: https://app.prolific.com/submissions/complete?cc=C4JGHDC0.Your total payment is: £0.70.
If you want to keep track of your payment, please keep your completion code.

Contacts & Final Report:
If you have questions or concerns about the study, you can contact the researchers at jonathan.norris@strath.ac.uk and agnese.romiti@strath.ac.uk.
Please be aware that you will break the confidentiality protocol. For more information and findings of the project, please visit https://sites.google.com/view/svyresults.

E Departures from Pre-Registered Analysis Plan

We list below figures and tables that were not pre-registered in the analysis plan, and explain our motivation behind conducing such analyses.

Section 3.5. Mechanisms for beliefs, extended analyses.

- We did not pre-register the splits by values of θs (columns 3 to 10) of Tables 5 or 6, nevertheless we deemed it important to understand how expectations about time investments and productivity of inputs varied by our measures of beliefs on absolute advantage.
- In Table 6, we did not pre-register the interactions between "Mother is free to help" and the additional two randomized features: (i) 1h30 *versus* 30 minutes of help, and (ii) both parents *versus* neither have a university education. These dimensions as randomized features were important for understanding variation in the effect of our key feature "mother is free to help".
- Table 7, expectations on parental education. We pre-registered the design, but only realized afterwards that looking at the full-time to part-time expected education gradient was the best way to analyze our question on parental education.
- Appendix, Table B.10, extended analysis on expectations about resource allocation. We did not pre-register the splits by values of θs, but we performed these to be consistent with Tables 5 and 6.

Section 4.2.1. Additional results on belief updating.

- Table 8, open-ended question. We departed from our pre-registered classification plan for the open-ended question described in Section 4, as we realized later that responses could be best coded to test our objective by "harmful to children when mothers work full-time", "not harmful", or "unclear answer". We also added a second classification to extract more detail.

- Appendix, Table B.7, information treatment effects robustness. We did not pre-register all of our robustness checks on the information treatment, nevertheless each of these provide a useful check to demonstrate our main results here are not sensitive.

- Appendix, Table C.3, perception gap. We did not pre-register the splits by values of θ for this perception gap analysis, but we performed these to be consistent through the paper.