Discussion Paper Series – CRC TR 224

Discussion Paper No. 722
Project A 03, C 01, C 02

Navigating Motherhood: Endogenous Penalties and Career Choice

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December 2025

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Support by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 is gratefully acknowledged.

Navigating Motherhood: Endogenous Penalties and Career Choice*

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November 2025

Abstract

Women strategically sort into "family-friendly" sectors characterized by lower returns to experience but also lower per-child penalties, before the birth of their first child. This pre-birth sorting represents an ex-ante career cost, a "sorting penalty" not captured by conventional measures. We build a heterogeneous agent model of career choice and fertility, incorporating both quality-quantity (Q-Q) and time-expenditure (T-E) trade-offs, to quantify this cost. Our central finding is that despite this sorting penalty being surprisingly small, it reveals an important mechanism: Women at the productivity margin are the switchers and use the Q-Q and T-E trade-offs as their primary, more powerful tools to navigate motherhood and career. Our findings highlight that frameworks excluding these trade-offs will overestimate the fertility responses and career costs associated with policies.

Key words: child penalty, fertility, sectoral gender segregation, job switch, quality-quantity trade-off

JEL Codes: E24, J13, J22, J24

*This paper has been previously circulated as "Child Penalties and Fertility across Sectors". In this paper, we use Administrative data from the Netherlands. Funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Projects A3, C1, and C2) and by Schoeller Foundation are gratefully acknowledged. We thank Matthias Doepke, Pia Heckl, Margarita Machelett, Nicola Fuchs-Schuendeln and Michele Tertilt for their guidance and the participants of the CRC Workshop, Luxembourg Gender and Economics Workshop, ASSET Conference, ESSIM CEPR Meetings, Mannheim Family Workshop, Oslo Macro Meetings.

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1 Introduction

Women suffer income losses compared to men after the birth of a child, known as "child penalties". While a significant body of work documents the heterogeneity of these penalties across countries and over time (Kleven, 2022; Kleven, Landais and Leite-Mariante, 2023), this paper argues that standard measures of these penalties miss a key component: the cost of ex-ante career choices women make before having children.

Women and men work in different types of occupations and sectors, and while occupational gender convergence has progressed (Blau and Kahn, 2017), sectoral segregation remains (Adsera and Querin, 2023) and even increases among married women (Alon, Coskun and Olmstead-Rumsey, 2025). We document a robust sorting pattern at the heart of this segregation. Women systematically sort into "family-friendly" sectors (e.g., healthcare, education) characterized by higher fertility, lower returns to experience (i.e., "linear" jobs, (Goldin, 2014)), and crucially, lower per-child penalties. This aligns with work by Erosa et al. (2022), which shows that home production time can account for sorting and wages, by Coskun and Dalgic (2024), linking the gender structure of the labor market to fertility outcomes, and by Alon, Coskun and Olmstead-Rumsey (2025), who find sectoral preferences are correlated with the fertility of women in that sector.

The "smoking gun" for this strategic behavior is that the sorting begins before the first child. Using administrative records from the Netherlands, we find that women have a significantly higher probability of switching into these family-friendly sectors than men, a difference that peaks in the years leading up to the first birth. We consider a high-stakes environment for such choices: the Netherlands has a high gender hours gap (Alon, Coskun and Olmstead-Rumsey, 2025) and one of the highest child penalties in Europe (47% Artmann et al., 2022), far exceeding countries like Denmark (20% Kleven et al., 2019b). This behavior reveals that women with higher fertility intentions are actively selecting career paths that, while offering lower wage growth, are more compatible with a larger family.

This pre-birth sorting represents an ex-ante cost of motherhood not captured by conventional child penalty estimates, which measure income loss only after a child is born. A central goal of this paper is to quantify this "sorting penalty." To do so, we build a heterogeneous agent model where women jointly choose their career (linear vs. non-linear), fertility, and investments in child quality (both time and money). The model is disciplined to match the empirical sorting patterns, sector-specific penalties, and fertility rates.

We use the model to conduct two key counterfactuals. First, we find that if women were forced to work in the high-penalty non-linear sector, the motherhood penalty would be 29% higher at the same fertility level. This quantifies the "price" of fertility that women are navigating. Second, we calculate the lifetime income loss from this strategic sorting. We compare our baseline to a counterfactual in which women choose their sector based only on productivity, ignoring family plans.

Our central finding is that this sorting penalty, i.e., the income lost from suboptimal career choice, is surprisingly small, accounting for only 2.5 percentage points of the total motherhood penalty. This is because women primarily use other margins: the quality-quantity trade-off and the time-expenditure trade-off. More specifically, fertility preference determines a woman's sectoral choice, and that sector, in turn, determines her "type of motherhood". We empirically show that women in linear sectors have more children and adopt a more time-intensive parenting style.

The importance of these adjustment margins is further highlighted in a counterfactual where we shut down the quality dimension, forcing women to choose only on quantity. Without the Q-Q and T-E margins, women are pushed into a choice between family and career. This dramatically increases fertility dispersion, as some women are forced to choose lower fertility to maintain a career, while others choose high fertility and face higher penalties. This polarization is absent in our full model, where the Q-Q/T-E tools allow women to navigate through family and career.

These trade-offs also have crucial implications for policy. We simulate a childcare subsidy (by lowering the price of quality). In the restricted model without quality, the subsidy acts as a per-child cash transfer, causing a large jump in fertility. In our full model, however, the fertility response is much lower because families use the subsidy to substitute towards higher quality children rather than just more children. This "quality-switch" channel provides a structural explanation for why many real-world childcare reforms have been found to have surprisingly small impacts on fertility (e.g., Kleven, Landais, Posch, Steinhauer and Zweimüller, 2024).

Our contribution is threefold. First, we provide new empirical evidence of strategic, anticipatory career switching by women years before their first child, a behavior mentioned as a possibility in studies like (Rabaté and Rellstab, 2022) but not, to our knowledge, explicitly documented before. Second, we are the first to quantify the cost of this sorting, showing it is small. Third, our model demonstrates why it is small, highlighting that the Q-Q and T-E margins are the primary mechanisms women use to navigate the trade-offs between motherhood and career.

Our work also contributes to a broader literature on the characteristics of female-dominated sectors and their role in work-family conflict. Studies show that women place a higher value on flexible work arrangements (Mas and Pallais, 2017), amenities (Faberman, Mueller and Şahin, 2025), predictability (Ciasullo and Uccioli, 2024) and that mothers receive lower returns to job characteristics, such as autonomy (Adsera and Querin, 2023). Our findings suggest that while sectoral sorting is important, the Q-Q and T-E trade-offs are the primary economic mechanisms for managing penalties within a chosen career. This distinguishes our findings from work that links penalties directly to sector-specific characteristics (Fontenay, Murphy and Tojerow, 2021) or firm-level policies (Bächmann, Frodermann and Müller, 2020).

Given that gender inequality is largely explained by motherhood (Kleven, Landais and Leite-Mariante, 2023) and that low fertility is a major policy concern (Albanesi, Olivetti and Petrongolo, 2023; Bloom, Kuhn and Prettner, 2023; Doepke, Hannusch, Kindermann and Tertilt, 2023), our paper shows that fertility decisions and career choices are deeply endogenous. Women with high fertility preferences are not passively penalized; they make active, strategic choices about their careers to realize their family goals. A thorough understanding of these trade-offs is crucial to address both gender inequality and low fertility.

2 Facts on fertility and child penalty across sectors

In this section, we summarize facts on fertility across sectors, sector characteristics, our findings from the child penalty estimation, and sector switches around the time of birth in the Netherlands. We focus on a sample of women and men, whom we can follow from five years before to eight years after the birth of their first child, covering all births between 2011 and 2015. Using employment records, we link these mothers and fathers to their employment histories, including any changes in their employment sectors. In total, we observe 499,713 mothers and 973,158 fathers, who are on average 29 and 31 years old, respectively. While around 24% of both women and men hold a university degree, only 3.5% of women but 34% of men hold a degree in the STEM field. The majority of women (60%) and around 26% of men are part-time employed, and around 39% of women and 35% of men have a fixed-term employment contract[1]. Our sectors are defined using the Statistical Classification of Economic Activities in the European Community (NACE 1st

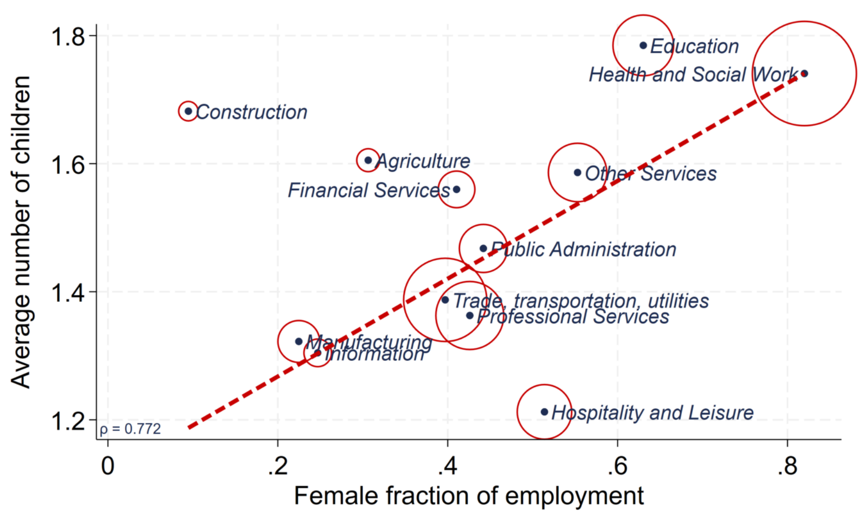
[1] For a more detailed description, see Section A.1.1. In Table A.1, we present for women (in column (1)) and men (in column (2)) sample characteristics.

level)[2].

2.1 Fertility across sectors

In Figure 1, we show that the female employment fraction on a sector level and the final number of children at the end of the observation period (in 2023) are highly correlated[3]. Women who work in more female-dominant sectors have more children on average. The strong relationship between fertility and female fraction across sectors remains when we focus only on the intensive margin (i.e., ever mothers) or adjust for the age composition (i.e., total fertility rate) (Figure A.1 and Figure A.2). As documented by (Alon, Coskun and Olmstead-Rumsey, 2025), women's preferences are associated with the average number of children across sectors. Hence, we interpret this fact as evidence that the job sorting behavior of women might be related to their fertility preferences.

Figure 1: Fertility and Female Share across Sectors



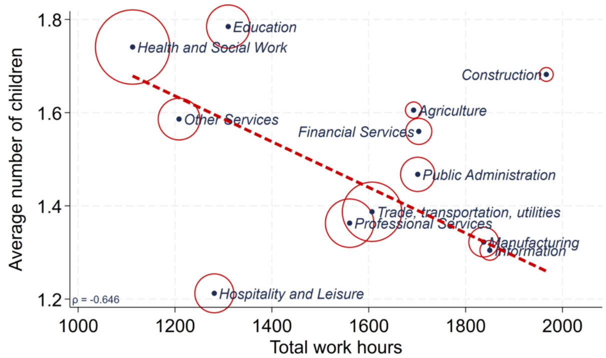
Notes: The figure plots the sector-level employment share of women and the total number of children (by the end of 2023), including the childless, i.e., the intensive margin and extensive margin are displayed jointly. We also report the weighted correlation coefficient by the sector size within female employment.

[2]NACE classification originally includes 21 sectors. Still, we regroup some small sectors that are closely related in terms of tasks/ topics and use 13. We exclude the mining (B) sector from our analysis due to the low number of observations. See Table A.2 for the definition of NACE sectors and how we re-group them.

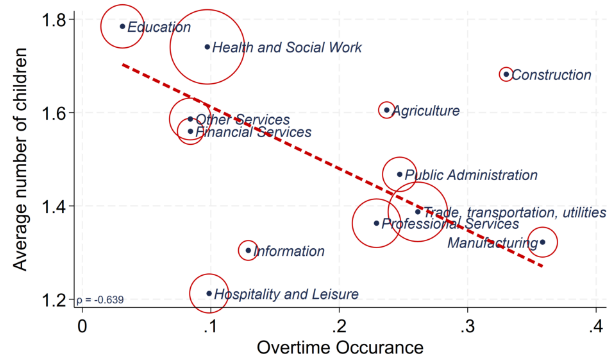
[3]We include childless men and women as well, so that the figure captures the intensive and extensive fertility margins. We pool the calendar years 2016 to 2018 of the employment records to recover the employment sector. We reweight the sectors according to their size within female employment to obtain a meaningful correlation coefficient of total fertility and female employment share.

2.2 Sector Characteristics

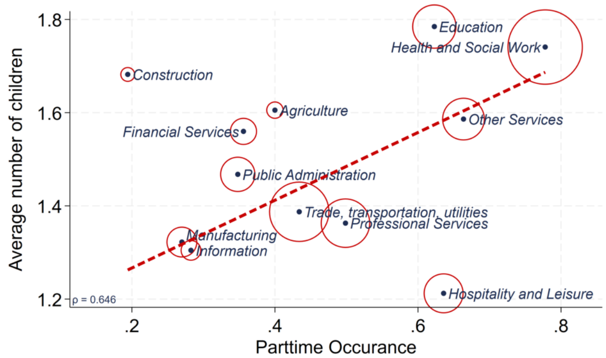
Figure 2: Sector Characteristics and Fertility



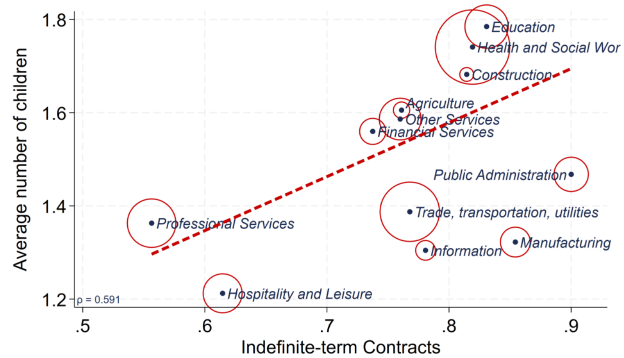
(a) Total Working Hours



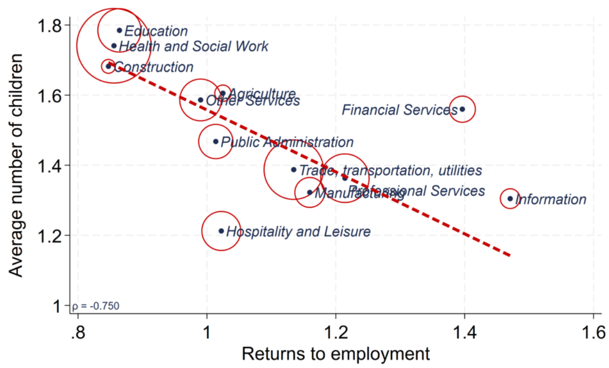
(b) Overtime Occurrence



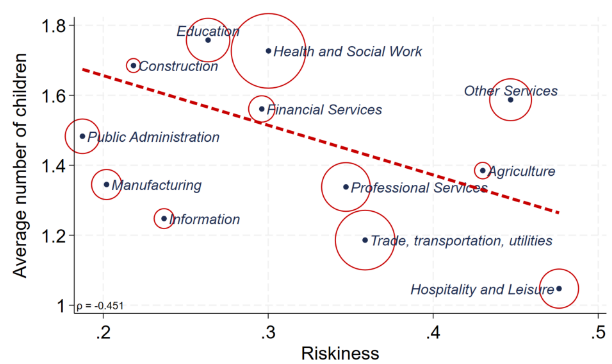
(c) Part-time employment



(d) Open-ended Contracts



(e) Returns to employment



(f) Riskiness

Notes: This figure shows how different employment characteristics correlate with the female employment share across sectors. Panel (a) annual working hours, panel (b) whether overtime occurs, panel (c) the share of part-time contracts, panel (d) the share of open-ended contracts, panel (e) returns to experience from a Mincerian regression, and panel (d) the riskiness measures as log wage growth. The sectors are reweighed according to sector size within female employment to obtain meaningful correlation coefficients (reported in the bottom left corner of each panel). See Appendix A.1.2 for details.

The sectors associated with higher fertility have a distinct set of economic characteristics. As shown in Figure 2, sectors with higher total fertility rates tend to exhibit, on average, lower total work hours (Figure 2a), less frequent overtime (Figure 2b), more part-time employment (Figure 2c), and open-ended contracts (Figure 2d). These characteristics are consistent with greater work-life flexibility, giving a clear incentive for women to sort into these sectors when planning a family. Gulek (2024) also shows that occupations with less part-time work are associated with higher penalties, and women select into occupations with part-time options.

Furthermore, these high-fertility sectors are also associated with lower returns to employment (Figure 2e) and lower wage risk (Figure 2f)[4]. The negative correlation implies that the long-term career cost of an interruption, such as maternity leave, is significantly smaller in high-fertility sectors, which could be driving the sorting behavior.

Taken together, these findings motivate a key distinction, in the spirit of Goldin (2014), between "linear" sectors that offer flexibility at the cost of lower wage growth, and "non-linear" sectors that offer higher returns but also impose larger penalties for time away from work. The structural model we develop in the following section is designed to capture this fundamental trade-off.

2.3 Child Penalty Across Sectors

To estimate child penalties, we built on the framework developed by (Kleven, Landais and Søgaard, 2019a) and estimate the following regression separately by gender (g):

$$Y_{ist}^{g} = \sum_{j \neq -1} \alpha_j^g I[t = j] + \sum_k \beta_k^g I[k = age_{is}] + \sum_y \gamma_y^g I[y = s] + \nu_{ist}^g \tag{1}$$

where Y_{ist}^{g} denotes the earnings of individual i, in calendar year s, at event time t. The first term captures a full set of event time dummies, where event time $t = 0$ marks the birth of the first child[5]. Figure A.3 and Figure A.4 report the results of child penalty estimation separately for each sector, by showing the variation in the results when different timing is assumed. Our findings align with Artmann, Oosterbeek and van der Klaauw (2022), who also investigate the heterogeneity of child penalties in the Netherlands and find substantial differences across fields of study. Polling all sectors, we find an overall child penalty

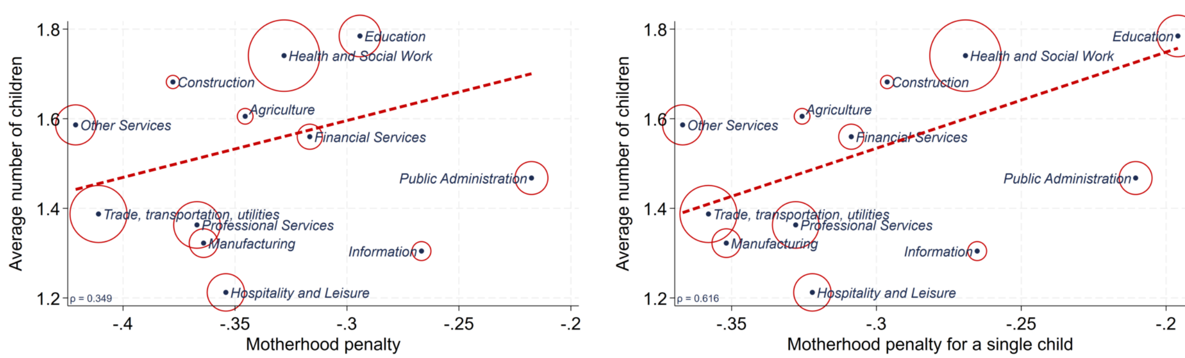
[4]See Appendix A.1.2 for a description of how returns and wage risk are measured/ defined.

[5]We compute motherhood (and fatherhood) penalties following (Kleven, Landais and Søgaard, 2019a), i.e., we estimate the loss in labor earnings eight years after the first child's birth relative to the mother's (or father's) labor income one year before the birth of the first child. More details can be found in Section A.2.

of around 37%, which is in line with recent findings for the Netherlands (see, e.g., Gan et al., 2025).

To understand how sectoral characteristics influence career costs, we compare motherhood penalties across sectors, distinguishing between mothers with one child and those with multiple children. This distinction is crucial because the decision to have subsequent children is endogenous and is likely influenced by the career costs experienced after the first birth. By disaggregating penalties by number of total children, we can investigate whether sectors with high initial penalties, for example, deter further childbearing (a selection mechanism) or impose a different cumulative penalty structure compared to low-penalty sectors.

Figure 3: Child Penalties and Fertility across Sectors



(a) Overall Penalty and Fertility

(b) One-Child Penalty and Fertility

Notes: The figure plots the sector-level employment share of women and the total number of children (by the end of 2023) including the childless, i.e., the intensive margin. We also report the correlation weighted by each sector's share of total female employment.

In Figure 3 we present the relationship of the motherhood penalty, i.e., the relative loss women face eight years after compared to one year prior to birth, and final fertility (as of 2023). Figure 3a shows a strong positive relationship, in that sectors with a lower motherhood penalty have, on average, higher total fertility rates. In Figure 3b, where the one-child motherhood penalty is used, this correlation intensifies (Figure A.5 reports the same figure for "per-child" penalties.). Specifically, women have more children in sectors where the penalty for the first child is smaller. This points directly to self-selection: women who intend to have larger families strategically sort into careers where the marginal cost of each child is lower. In Figure 4, we document that these are precisely the "linear" sectors, characterized by lower returns to employment and riskiness, and thus a lower expected motherhood penalty. This highlights the endogeneity of fertility and child penalties; comparisons across groups can be misleading without accounting for the fact that women are actively choosing both their career paths and their family size.

Figure 4: One-Child Penalties and Sector Characteristics

(a) One-Child Penalty and Returns to Emp.

(b) One-Child Penalty and Riskiness

Notes: The figure plots the sector-level one-child motherhood penalties and returns to employment in panel (a) and one-child motherhood penalties and riskiness in panel (b). For a detailed description on the returns and riskiness measure, see Appendix A.1.2. We also report the weighted correlation coefficient by the sector size within female employment.

2.4 Sector Switch around Birth

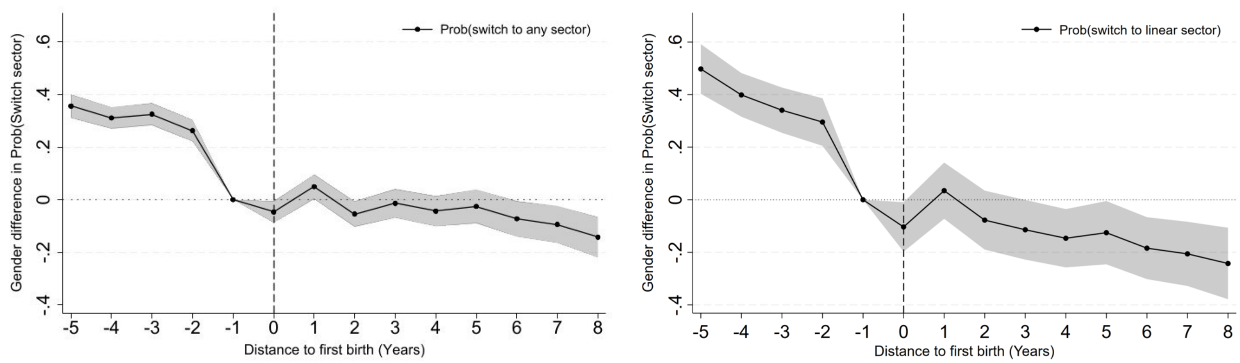
We are interested in how women and men switch between sectors (or groups of sectors) around the time of their first birth. For this purpose, we extend the framework developed by Kleven, Landais, Posch, Steinhauer and Zweimüller (2019b) as follows:

$$
\begin{aligned}
Y_{ist} = & \sum_{j=-5, j\neq -1}^{8} \alpha_j I[t=j] + \sum_{j=-5, j\neq -1}^{8} \alpha_j^F \left(I[t=j] * female\right) \\
& + \sum_k \beta_k I[age=k] + \sum_k \beta_k^F \left(I[age=k] * female\right) \\
& + \sum_s \gamma_s I[year=s] + \sum_s \gamma_s^F \left(I[year=s] * female\right) \\
& + \delta female + \nu_{ist}
\end{aligned} \tag{2}
$$

where Y_{ist} indicates whether i switched the employment sector, in calendar year s, at event time t. The coefficients of interest are the α_j^F's capturing the difference in women's vs. men's probability of switching to another sector (or to a linear sector). To scale the effects (and gender differences), we convert the coefficients into percentage changes due to the arrival of the first child[6]. We plot the gender difference in the average decrease in the switching probability relative to one year before the first child's arrival in Figure 5. Panel a considers the probability of switching to any sector, and panel b focuses on the probability of switching to a linear sector.

It is important to note here that switching behavior, as opposed to the evolution of earnings (around birth), is an endogenous decision, for which causal identification in a reduced form is challenging. Here, we are interested in documenting how switch probabilities around the birth of the first child differ by gender (Figure 5) and within gender by fertility preferences (Figure 6), net of any life cycle and time trends.

Figure 5: Sector Switching around Birth



(a) Any Sector

(b) Linear Sectors

Notes: The graphs plot the α_j^F's of regressions estimated using specification (2). In panel (a), the switch to any sector, and in panel (b), the switch to a linear sector is considered. We define linear sectors as P (Education), Q (Human Health and Social Work Activities), S (Other Service Activities) and K (Financial Services). See Appendix Table A.3 for the definition of linear sectors.

We find that women, compared to men, have a significantly higher likelihood of switching sectors before birth, which is driven by the switch to linear sectors (education, health, and other services) as shown in Figure 5b. Furthermore, we observe that the differential switch probability to linear sectors peaks five years before birth and remains positive. In particular, the average probability of switching sectors one year prior to birth is 9.44%[7]. As shown in Figure 5b, before the birth of the first child, women, compared to men, are more than 20% more likely to switch sectors relative to one year before birth. However,

[6] We employ the percentage loss conversion as in the conventional child penalty estimation by comparing the coefficients (here α_F) to the predicted outcome (here switch probability), in the absence of the first child.

[7] In Figure A.6 and A.8 we plot average switch probabilities around the first birth for both women and men.

these gender differences disappear after birth (although the switch probabilities for both genders remain positive). The higher switch probabilities are mainly driven by switches into linear sectors, as shown in Figure 5b. These results suggest that women exhibit strategic behavior when planning their first and subsequent children[8].

Next, we analyze differential switches to female sectors for mothers and fathers with one vs. more children. To do this, we adjust the specification (2)[9]. We interact the event dummies with an indicator for having one child only (vs. more) and an indicator for being employed in a linear sector (vs. non-linear sector)[10]. Figure 6 reports these triple interaction coefficients, i.e., the differential switching probability of mothers (in red triangles)/ fathers (in black squares) who have one vs. more than one child at the end of the observation period, and whether the mother/ father switches to a linear or a non-linear sector. Again, we translate the estimated coefficient into percentage changes relative to one year before the first child's birth, where the probability of switching sectors is on average 10.94%. Before the birth of the first child, we find small differences in the switch probability relative to one year prior to birth between women with different fertility preferences. However, after the birth of the first child, women who ultimately have more than one child are more likely to switch to linear sectors than to other sectors compared to women with only one child[11]. Assuming that higher fertility reflects stronger fertility preferences, this result suggests that women with strong fertility preferences self-select into linear sectors[12]. This selection seems to intensify strongly around two years after the birth of the first child. Furthermore, although fathers who ultimately have more than one child also exhibit a similar pattern, the pattern is a bit flatter, and the differences are smaller in magnitude.

[8]In Figure A.7, we show the exact switching patterns of women before the birth of the first child. The majority of switching comes from women starting in sector M (Professional Services) and switching to sectors D (Trade, Transportation, Utilities) and Q (Health and Social Work). Women are switching towards sectors with higher total fertility and who are bigger in terms of female employment.

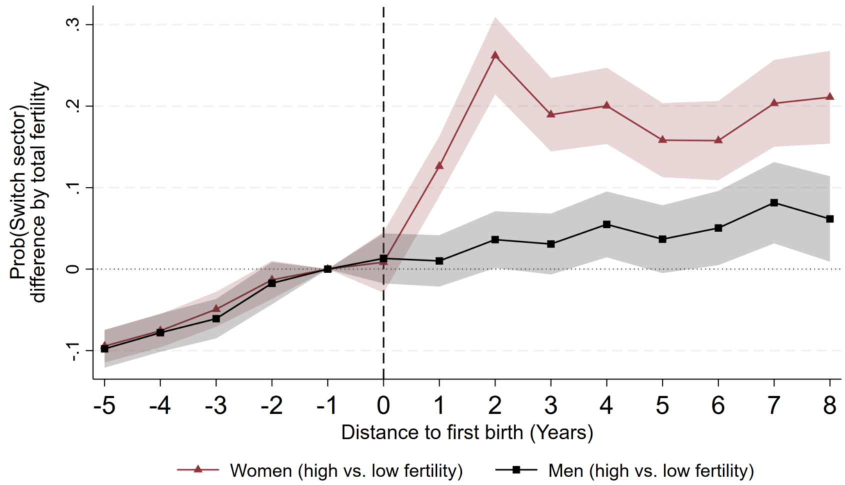
[9]See Appendix A.2 for details on the specification and estimation.

[10]We use a fully interacted model, i.e., controlling for the interacted time- and life-cycle trends.

[11]The numbers plotted here report a triple interaction. For example, the red triangle at 2 indicates that women with higher fertility preferences (i.e., with more children at the end of the observation period) are on average 24% more likely to switch to a linear sector rather than other sectors compared to women with lower fertility preferences measured relative to their switch probability one year before birth.

[12]Even though it is possible for parents of single-children to have strong fertility preferences, using the administrative data, this is the only measure available. In Figure A.9, using the LISS Dutch household survey, we show that desired fertility and actual fertility across sectors are (strongly and) positively correlated.

Figure 6: Switch to Linear Sectors



Notes: The graph plots the triple interaction coefficients from an extension of specification 1 in which we interact the entire model with a dummy for having multiple vs. one child and switching to a linear vs. another sector, with switches as an outcome. Coefficients are translated into percentage changes relative to one year before the birth of the first child. We define linear sectors as P (Education), Q (Human Health and Social Work Activities), S (Other Service Activities), and K (Financial Services).

3 Model

In this section, we build a heterogeneous agent model of fertility and industry choice to quantify how fertility preferences and career trade-offs jointly determine sector choice, switching patterns, and endogenous child penalties.

Our model is motivated by several empirical facts. We observe that sectors with high female employment and high fertility tend to have lower returns to experience (Figures 2 and 4). Furthermore, we see women switching to these "linear" sectors both before and after childbirth (Figures 5 and 6). Our model is designed to capture these selection patterns, delivering an estimate of child penalties that accounts for this endogenous sorting.

The model is a two-period framework in the spirit of Erosa et al. (2022) and Adda et al. (2017), featuring two sectors: **Linear** and **Non-linear** (Goldin, 2014). Women live for two periods and make decisions regarding consumption (c_t), saving (b_0), fertility (n_t), child quality (q_t), and which industry to work in (s_t). Agents are heterogeneous in their fertility preference (γ_i) and their sector-specific productivity (z_{sit}). For the full set of model equations refer to Section A.5.3.

3.1 Preferences and Constraints

A woman's time endowment in each period is normalized to one. Labor supply (l_t) is what remains after time costs for children:

$$l_t = 1 - (h_t + \tau)n_t$$

where τ is the fixed time cost per child and h_t is the *chosen* time investment (part of quality) per child.

Women solve the following maximization problem:

$$\max_{c_t, b, n_t, q_t, e_t, h_t} V = \log(c_0) + \gamma_i U(n_0, q_0) + \beta \log(c_1) + \beta^f \gamma_i U(n_1, q_1)$$

where the utility from family $U(n, q)$ is given by

$$U(n, q) = \frac{(\alpha n^\rho + (1-\alpha) q^\rho)^{\frac{1-\eta}{\rho}}}{1-\eta}$$

Utility is derived from consumption and a CES-nested bundle of child quantity (n) and quality (q). We allow for different time preferences for consumption (β) and children (β^f) to capture, for example, the observed high average age at first birth. The parameter α is the weight on quantity, ρ governs the Q-Q substitution, and η is the curvature of the child utility function.

Child quality (q_t) is a CES-combination of time (h_t) and monetary (e_t) inputs (Caucutt et al. (2020)):

$$q_t = \left(\omega h_t^{1-\sigma} + (1-\omega) e_t^{1-\sigma}\right)^{\left(\frac{1}{1-\sigma}\right)}$$

The budget constraints in each period are:

$$c_0 + \bar{w}(e_0 + \bar{e})n_0 + b_0 = w_0 l_0$$
$$c_1 + \bar{w}\left(e_1 + \bar{e}\right) n_1 = w_1 l_1 + b_0 R$$

where w_t is the hourly wage, l_t is labor supply, R is the return on savings, $\bar{w}$ is the exogenous price of child-related goods, and $\bar{e}$ is a fixed resource cost per child.

3.2 Endogenous Wages and Human Capital

A key feature of our model is the endogenous wage process, where human capital is accumulated through work experience. The hourly wage $w_{s,i,t}$ in sector s depends on productivity $z_{s,i,t}$ and labor supply choices:

$$w_{s,i,0} = z_{s,i,0} \left(l_{i,0}\right)^{\mu_s}$$
$$w_{s,i,1} = z_{s,i,1} g_{s,i} (l_{i,1})^{\mu_s} \tag{3}$$

Wage growth into the second period, $g_{s,i}$, is defined as:

$$g_{s,i} = (g \cdot z_{s,i,0} l_{i,0})^{\mu_s}$$

This specific formulation is central to our mechanism. The sector-specific parameter μ_s **governs the returns to working** and does two things simultaneously:

1. **Returns to Hours (Current Period):** It defines the non-linearity of the *current* wage. A $\mu_s > 0$ implies that working fewer hours ($l_t < 1$) reduces the hourly wage, capturing the penalty for part-time work or interruptions.

2. **Returns to Experience (Future Period):** It *also* governs the accumulation of human capital. Labor supply in period 0 ($l_{i,0}$) builds experience, which directly increases the wage growth term $g_{s,i}$ and thus the wage in period 1[13].

Following Goldin (2014) and Erosa et al. (2022), we define **"linear" sectors** as those with a low μ_s and **"non-linear" sectors** as those with a high μ_s. This structure creates the model's core trade-off: non-linear sectors offer higher potential earnings (steeper wage profiles) but impose a larger wage penalty for time taken out of the labor force for child-rearing, both in the current and future periods.

3.3 Endogenous Child Penalties

Our model features endogenous child penalties from three sources:

1. **Time Cost:** Children require time (h_t and τ), which mechanically reduces labor supply l_t.

2. **Returns to Hours/Experience:** Reduced labor supply l_t leads to a lower hourly wage in the current period and lower human capital accumulation for the future, an effect that is magnified in non-linear sectors (the μ_s mechanism).

[13] As shown by Fischer et al. (2025), the human capital accumulation margin is responsible from the glass ceiling.

3. **Sector Choice:** Women with high fertility preferences (γ_i) may **self-select** into the linear sector, accepting a flatter wage profile to reduce the career-related child penalty.

3.4 Calibration

We calibrate the model to match key features of the Dutch labor market and fertility patterns. We assume one model period is 15 years, with women aged 20-35 in the first period and 35-50 in the second.

Model Parameters

The model parameters, shown in Table 1, are determined in three ways:

1. **Externally Set:** We fix the time discount factor $\beta = 0.900$ as is standard. The key sector-specific returns-to-work parameters, $\mu_l = 0.200$ and $\mu_n = 0.600$, are taken directly from Erosa et al. (2022). The fixed time (τ) and goods ($\bar{e}$) costs of children are assumed.

2. **Directly Estimated from Data:** We set the income growth parameter $g = 2.000$ to match overall wage growth in our data. The standard deviations of sector-specific productivity, $\sigma(z_l)$ and $\sigma(z_n)$, are set to 0.352 to match the wage dispersion observed for men (who are not subject to the same selection on fertility). The mean linear productivity $\bar{z}_l$ is normalized to 1.

3. **Internally Calibrated:** The remaining parameters are calibrated jointly using a simulated method of moments to match the data targets in Table 2. The parameters governing fertility preferences ($\tilde{\gamma}$, γ_f, $\sigma(\gamma)$) are primarily identified by fertility levels, timing, and dispersion. The Q-Q and T-E trade-off parameters (α, ρ, σ, $\bar{w}$) are disciplined by the observed penalties and the sorting of women with different fertility levels. The heterogeneity parameters ($\bar{z}_n$, and the covariance matrix Σ) are chosen to match the fraction of women in each sector, the switching probabilities, and the sector-specific penalties and fertility rates.

Variable	Description	Value	Source
β	Time Discount Factor	0.900	Standard
R	Gross Interest Rate	1.111	Derived
γ_f	Fertility Taste Shifter (P2)	3.922	Calibrated
η	Fertility Curvature	1.024	Calibrated
$\bar{\gamma}$	Fertility Taste Mean	0.842	Calibrated
α	CES Quantity Weight	0.234	Calibrated
ρ	CES Elasticity Parameter	0.757	Calibrated
σ	Elasticity of Q Production	3.320	Calibrated
ω	Time Share in Q Production	0.563	Calibrated
τ	Fixed Time Cost	0.010	Assumed
$\bar{e}$	Fixed Goods Cost	0.050	Assumed
$\bar{w}$	Price of Quality	2.200	Calibrated
μ_l	Linear Sector Returns	0.200	Erosa et al. (2022)
μ_n	Non-Linear Sector Returns	0.600	Erosa et al. (2022)
g	Income Growth	2.000	Data (Wage Growth)
$\bar{z}_l$	Linear Sector Prod. Mean	1.000	Normalized
$\bar{z}_n$	Non-Linear Sector Prod. Mean	1.158	Calibrated
$\sigma(z_l)$	Linear Sector Prod. Std.	0.352	Data (Wage Dispersion)
$\sigma(z_n)$	Non-Linear Sector Prod. Std.	0.352	Data (Wage Dispersion)
$\sigma(\gamma)$	Fertility Taste Std.	0.886	Calibrated

Table 1: Parameters

Targeted Moments

Table 2 presents the full set of targeted moments, which discipline the model's key mechanisms. We target not only aggregate outcomes (overall fertility, penalty) but also the crucial sorting patterns and cross-sectional moments that are the focus of our paper. For details of model simulation, see Section A.5.1.

The model provides a close fit to the data. It successfully replicates the overall motherhood penalty (-0.42 and -0.41 in the data and the model) and the average fertility levels across both periods. Most importantly, the model endogenously generates the key sorting patterns observed in the data: compared to women in non-linear jobs, women in linear jobs have both higher fertility (1.71 vs. 1.63 in the model) and a lower motherhood penalty (-0.38 vs. -0.44 in the model). This confirms the model's ability to capture the central trade-off of our analysis. The main discrepancies are in the standard deviation of fertility, which the model under-predicts (0.39 vs 0.81), and the probability of switching, which it over-predicts (0.22 vs 0.12).

Moment	Definition	Data	Model
n_0	Fertility in period 0	0.55	0.59
n_1	Fertility in period 1	1.07	1.08
$P(nonlinear)_1$	Fraction women in nonlinear (period 1)	0.46	0.57
$P(switch\|nonlinear)$	Prob. switch if nonlinear in period 0	0.12	0.22
Penalty	Motherhood Penalty	-0.42	-0.41
$\sigma(n_{tot})$	Std. of total fertility	0.81	0.39
Penalty (Linear)	Penalty for women in linear jobs	-0.33	-0.38
Penalty (Non-Linear)	Penalty for women in nonlinear jobs	-0.44	-0.44
n_{tot} (Linear)	Fertility for women in linear jobs	1.73	1.71
n_{tot} (Non-Linear)	Fertility for women in nonlinear jobs	1.50	1.63

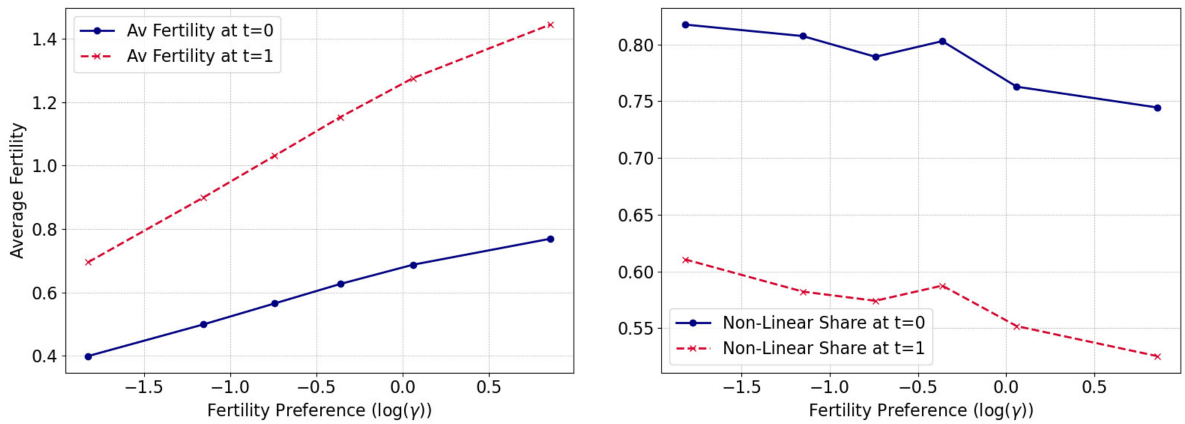
Table 2: Data Targets

4 Results

In this section, we emphasize the significance of sector choice and the quality-quantity trade-off in our model. We first demonstrate that women with a strong preference for fertility tend to work in the linear sector, both initially and as they transition to the linear sector in the second period. Second, we show the implied child penalty in the absence of family consideration. Third, we demonstrate both quantitatively and empirically quality-quantity and time-expenditure tradeoffs. Finally, we show how fertility and child penalty would be in a hypothetical world where women switch sectors while keeping either their fertility or child penalty unaffected.

4.1 Sector Choice and Fertility

In our model, sorting is driven by heterogeneous fertility preferences (γ_i). As shown in Figure 7a, women with a higher γ_i have higher fertility in both periods. This preference directly maps to their career choice. Figure 7b shows that women with higher fertility preference are less likely to work in non-linear sectors and, if they start there, are more likely to switch to the linear sector. The mechanism is intuitive: women who place higher utility on children (high γ_i) self-select into more 'family-friendly' sectors. In our framework, family-friendliness is defined by the parameter μ_s, which represents the "price" of working less. Women sort into the linear sector (low μ_s) where time away from work is penalized the least.[14]



(a) Fertility

(b) Sector Choice

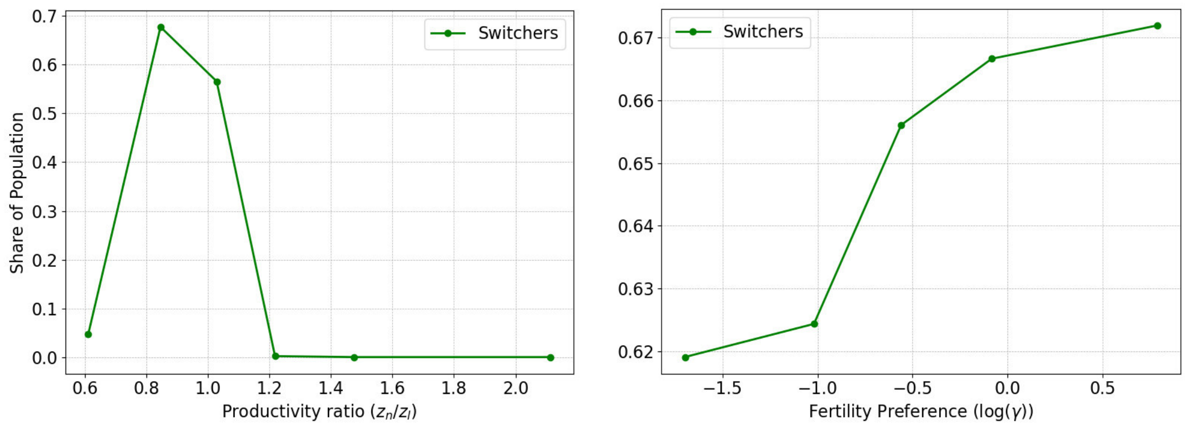
Figure 7: Fertility and Sector Choices with respect to preferences

Our model also allows for dynamic career choices via switching. Figure 8a shows who is on the margin to switch. The probability of switching is highest when an individual's productivity in the linear and non-linear sector is similar (i.e., when the ratio z_n/z_l is close to one). Women with a strong comparative advantage in one sector (a very high or low ratio) remain there.

Figure 8b shows why these "on the fence" women ultimately switch. By focusing only on this high-switching group, a clear positive relationship is revealed: a stronger preference for fertility (γ_i) directly increases the probability of switching from the non-linear to the linear sector.

In line with our empirical evidence (Section 2), the model identifies a specific type of woman who switches careers: one who is productive in both sectors but also has a high desire for a family. The optimal strategy for this woman is to front-load her career. She starts in the high-growth, non-linear sector to accumulate human capital, then switches to the more flexible, linear sector to have children, thereby mitigating the long-run wage penalty of motherhood.

[14] We replicate this exercise for industry productivity z_n and z_l in Section A.5.2



(a) Overall

(b) Across Sectors

Figure 8: Switch Probabilities

Notes: Figure plots the trend-lines coming from plotting quality and quantity choices from simulations. In order to reduce the variability coming from fertility preference, we focus on women with fertility preference between 40-60 percentiles.

4.2 Motherhood Penalties Related to Sectoral Choice

Our model simulations reveal a sorting mechanism based on both preferences and productivity. As shown in Figure 7b, women with a higher fertility preference (γ_i) are significantly more likely to sort into the linear sector. Furthermore, the decision to switch from the non-linear to the linear sector is most common among women whose productivity in both sectors is similar, with the switching probability peaking when the productivity ratio (z_n/z_l) is close to one (Figure 8a). Since fertility preference is orthogonal to productivity in our model, these findings imply that a specific group of women; those with high fertility desire but no strong comparative advantage in a single career, are willing to forgo the higher wage growth of the non-linear sector to have more children.

This raises a key quantitative question: what is the lifetime income cost of this strategic sorting? Standard empirical estimates of the motherhood penalty do not capture this ex-ante career choice. We use our model to conduct a counterfactual analysis. We calculate a "regular" penalty (the income loss within a chosen career) and a "total" penalty, which compares a woman's outcome to a hypothetical scenario where she chooses the career that maximizes her lifetime income, ignoring family concerns.

We find that the total motherhood penalty is -42%, only 2.5 percentage points larger than the regular penalty. This small number is a central finding of our paper. It demonstrates that the direct productivity loss from industry choice is minimal precisely because women have other, more powerful tools at their disposal. They primarily use the quality-quantity and time-expenditure trade-offs to mitigate career costs.

Table 3 demonstrates this clearly by focusing on the "high productivity, high fertility preference" group. Women who stay in the non-linear sector mitigate their penalty by having fewer children (1.33) than their linear-stayer counterparts (1.40). Most importantly, they achieve a similar level of child quality ($q_1 = 0.12$) by adopting a starkly different input mix, substituting away from their own expensive time and towards purchased goods. Non-linear stayers have the lowest time investment ($h_1 = 0.23$) and the highest monetary expenditure ($e_1 = 0.26$) of any group, allowing them to minimize their penalty (-0.71) relative to what it would be otherwise.

	Fertility (n_1)	Quality (q_1)	Expenditure (e_1)	Time (h_1)	Penalty	Fert. Delay (n_1/n_0)
Linear (Stayers)	1.40	0.12	0.24	0.26	-0.62	1.86
Non-linear (Stayers)	1.33	0.12	0.26	0.23	-0.71	1.81
Switchers (NL to L)	1.35	0.11	0.25	0.24	-0.58	1.90

Table 3: Quality-Quantity & Time-Expenditure Tradeoff by High Productivity Women with High fertility preference

Notes: High productivity means $z_{1,i}$ larger than the median among simulations, regardless of the sector. Similarly, high fertility preference takes women with γ_i larger than the median. Table plots fertility and quality of women whose both productivity and fertility preferences are larger than the median.

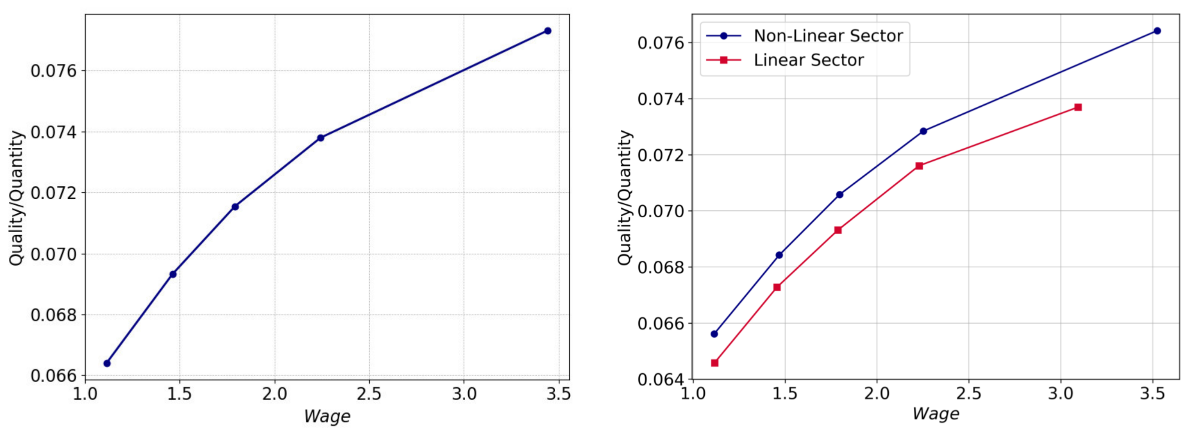
In the model, fertility decisions and sectoral choice are jointly determined. Fertility preferences influence sectoral selection (Figure 7b), while wages and sector-specific productivity shape fertility investments (Table 3). High-earning women with strong fertility preferences allocate more resources to their families, but they optimize this investment by prioritizing expenditure over time, thereby minimizing career sacrifices. This trade-off allows them to maintain high productivity in non-linear sectors while investing in their family. Below, we explain these channels in detail, providing empirical evidence.

4.3 Quality-Quantity Trade-off

The fertility decision is linked to quality investment made for children (Doepke (2015)). It has been shown that there is a negative fertility-income relationship (Jones et al. (2010)) and a positive quality-income relationship. However, the extent of the trade-off between quality and quantity of children has changed recently due to a lower education gradient on fertility decisions (Doepke et al. (2023)) and due to marketization (Bar et al. (2018)). In other words, the number of children does not vary as much with respect to income or education as it did in previous cohorts. This observation crucially depends on how flexible families are in the quality-quantity trade-off.

Our model provides key insights into the quality-quantity (Q-Q) trade-off by accounting for heterogeneity in both fertility preferences and career paths. Figure 9a shows that the model generates a positive relationship between wages and the quality-quantity ratio. This indicates that as women's income increases, their child-rearing strategy shifts systematically towards higher quality per child.

Figure 9b decomposes this relationship by sector. While the positive relationship holds for both groups, the curve for the non-linear sector is both steeper and higher than for the linear sector. This highlights two important findings. First, for any given wage level, women in the non-linear sector choose a higher quality-to-quantity ratio. Second, as wages rise, this ratio increases more sharply for them.



(a) Overall (b) Across Sectors

Figure 9: Quality-Quantity Trade-off

Notes: Figure plots the trend-lines coming from plotting quality and quantity choices from simulations. In order to reduce the variability coming from fertility preference, we focus on women with fertility preference between 40-60 percentiles.

The economic mechanism driving this difference is the higher return to experience in the non-linear sector. Since time away from work is more costly for these women, they have a stronger incentive to substitute away from time-intensive child quantity and towards quality that can be purchased with goods. The flatter slope for the linear sector suggests that the Q-Q trade-off is less binding for these women; as their wages rise, the shift towards quality is less pronounced. This differential trade-off, driven by career choice, has important implications for inequality in human capital investment, consistent with the findings of De La Croix and Doepke (2003).

We further provide empirical evidence for higher-quality investments among mothers working in non-linear sectors in Table 4. We use Dutch administrative data to link mothers' sector of employment to their children's standardized educational outcomes. Table 4 presents OLS regressions where the dependent variables are key proxies for child quality: the final primary school CITO test score, its Math and Language sub-scores, and a binary indicator for a recommendation to the "High track" in secondary school.

	CITO score	Math	Language	High track
Non-linear	0.439***	0.751***	0.309***	0.018***
	[0.051]	[0.062]	[0.073]	[0.003]
Work hours (log)	-2.416***	-2.672***	-2.965***	-0.097***
	[0.070]	[0.085]	[0.099]	[0.004]
Income (log)	2.357***	2.645***	2.864***	0.095***
	[0.061]	[0.074]	[0.086]	[0.004]
Year fixed effects	Yes	Yes	Yes	Yes
N	132640	96092	96092	132640
R2	0.089	0.398	0.166	0.042

Table 4: Education of children

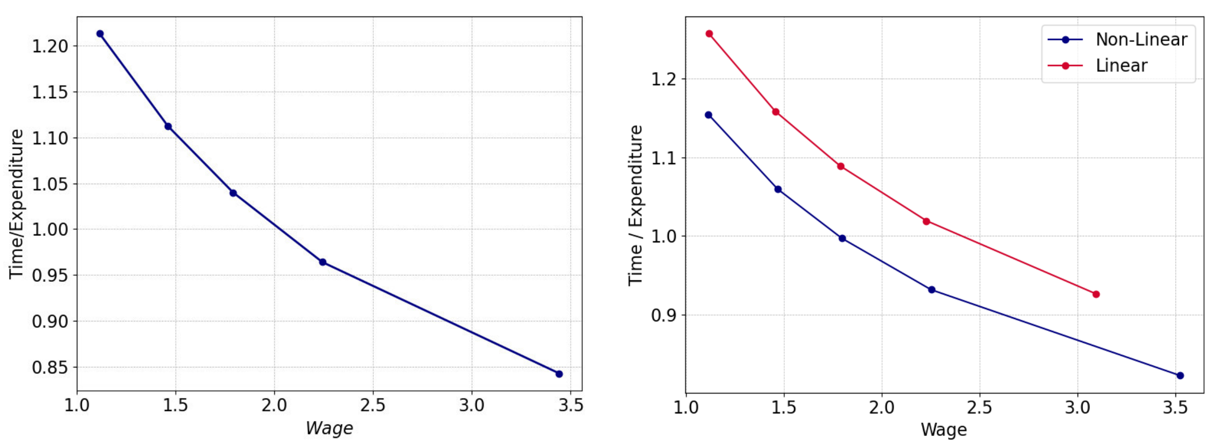
Notes: The Cito test *is a standardized test administered at the end of primary school (age 12/13), to determine the secondary school track children will be admitted to. All regressions include controls for age, education, and the number of children.*

The results strongly support the mechanism of our model. After controlling for log income, log work hours, parental education, age, and year fixed effects, the coefficient on the non-linear sector dummy is positive and highly significant across all four quality measures. This indicates that the choice of a non-linear sector is associated with higher child quality, even after accounting for the direct effects of income and time use. The effect is also economically meaningful: working in a non-linear sector is associated with a 1.8 percentage point higher probability of a child being admitted to the high track. This confirms the model's prediction that women in non-linear careers adopt a higher-quality child-rearing strategy. This finding, combined with the fact that these women have fewer children on average (see Figure 1), provides strong empirical validation for the quality-quantity trade-off being a key mechanism of self-selection across sectors.

4.4 Time-Expenditure Trade-off

In our model, women choose not only between child quality and quantity, but also the composition of that quality, i.e., whether to allocate parental time or monetary expenditure. Figure 10a illustrates this mechanism, showing a clear negative relationship between wages and the time-to-expenditure ratio. As their opportunity cost of time rises, higher-wage women substitute away from time investment and towards expenditure on goods to mitigate career penalties.

Figure 10b decomposes this relationship by sector. The trade-off is present in both career tracks; more importantly, the curve for the linear sector is consistently above that of the non-linear sector. This suggests that, at any given wage, women in linear careers use a more time-intensive input mix for child quality. On average, women in the linear sector rely more heavily on time than on goods (a ratio greater than one). In contrast, high-earning women in the non-linear sector reverse this pattern, spending more on goods than they invest in time.



(a) Time-Expenditure Trade-off

(b) Across Sectors

Figure 10: Time-Expenditure Trade-off

To provide empirical support for this trade-off in our model, we use the 2010 wave of the Harmonised European Time-Use Survey (HETUS) for Germany, France, and the UK[15].

[15] The data for the Netherlands in HETUS do not provide sector information; therefore, we use a pooled regression for these major countries. In Appendix Table A.7, we also provide a more limited analysis with

Table 5 presents our regression results, where the dependent variable is the amount of time mothers spend on childcare per child.

The results provide strong evidence in support of our model's mechanisms. First, we find a significant sorting effect: the coefficient on the linear sector dummy is positive and significant, indicating that women in these careers spend substantially more time with their children. This effect is particularly strong for, and driven by, time spent with young children (ages 0-7), as shown in column (2).

	All Care per child			Quality Care	Basic Care
	All Children	Young Children	Older Children	All Children	All Children
Linear	3.839**	8.435***	-0.521	1.679**	2.160*
	(0.011)	(0.004)	(0.645)	(0.026)	(0.070)
HH Income Quantile	-6.280***	-0.185	-4.669***	-2.276***	-4.004***
	(0.000)	(0.909)	(0.000)	(0.000)	(0.000)
Work Hours	-0.595***	-0.876***	-0.137***	-0.162***	-0.433***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
N	7204	2875	4329	7204	7204
R2	0.184	0.213	0.034	0.067	0.171

Table 5: Time with Children

Notes: Data is from Harmonized European Time-Use Survey, wave 2010. Countries are the UK, France, and Germany. All regressions include controls for age, education, and the number of children. Young children are between the ages of 0 and 7, and older children are between the ages of 7 and 17. See Table A.6 for total care time for all children, and Table A.5 for alternative regression specifications.

Second, the results highlight the key constraints women face. Both higher household income and longer work hours are strongly and negatively associated with time spent on childcare. While we do not directly observe monetary investments, the negative coefficient on income suggests a time-expenditure trade-off: as a household's resources increase, mothers substitute away from direct time investment, which is consistent with them purchasing other inputs for their children. Further, in Appendix Table A.4, we show that women in linear sectors, on average, have a higher number of children. In line with

the LISS Panel for the Netherlands. Due to sample size and data limitations in LISS, we present the HETUS results as our primary benchmark; however, findings from the smaller Dutch sample are consistent with the pooled results.

our model, these findings from the HETUS data confirm that women in linear sectors have, on average, more children and adopt a more time-intensive motherhood style.

4.5 Fertility vs. Penalty

Figure 11 plots the counterfactual trade-off frontier between fertility and the motherhood penalty for the linear and non-linear sectors. This trade-off is shaped by the model's mechanisms: women in the linear sector, for instance, spend more time with their children (versus expenditure) and incur lower penalties for any given level of fertility due to the sector's lower returns to hours.

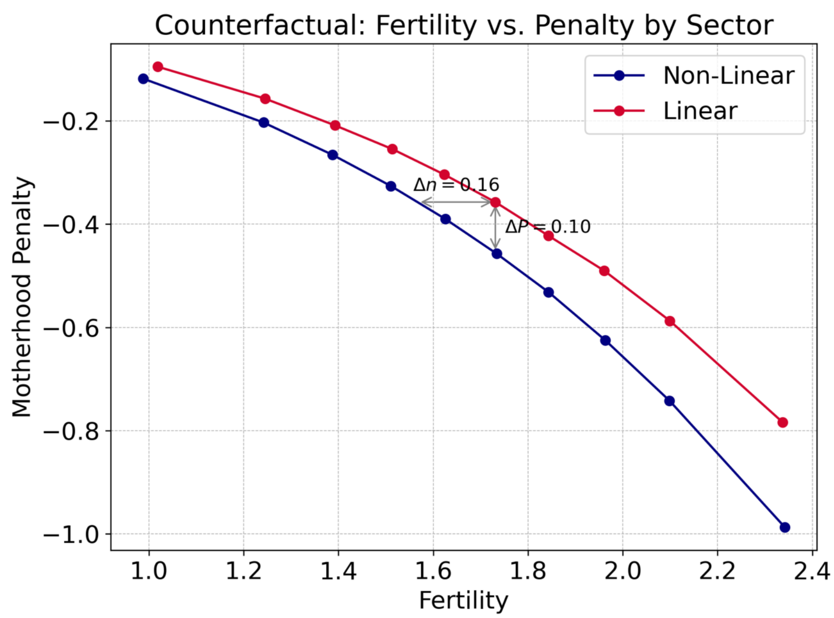


Figure 11: Motherhood Penalty

Notes: The figure plots the counterfactual trade-off frontiers between fertility and the motherhood penalty for the linear (red) and non-linear (blue) sectors. Each point on the lines represents a quantile of the model simulations. The arrows illustrate the counterfactual trade-offs, originating from the median linear-sector outcome (the 50th percentile point on the red line). The vertical arrow ($\Delta P = 0.10$) shows the additional penalty the median linear-sector woman would face if she were in the non-linear sector but kept her fertility level constant. The horizontal arrow ($\Delta n = 0.16$) shows the reduction in fertility the same woman would need to accept to maintain her original penalty level if she were in the non-linear sector.

The figure allows us to quantify the "price" of fertility in each sector. For example, forcing a woman with median preferences from the linear to the non-linear sector, while holding her fertility fixed at 1.7, would increase her motherhood penalty by 10 percentage points

($\Delta P = 0.10$). Alternatively, if we forced her to maintain the same penalty level, her fertility would have to be 0.16 lower ($\Delta n = 0.16$) in the non-linear sector.

This highlights the core endogeneity of sector choice. The two frontiers represent the "menu of prices" available to women. A woman with a strong preference for family will find it optimal to self-select into the linear sector, where the "price" of each child (in terms of career penalty) is lower. Conversely, a woman with a strong career preference may select the non-linear sector, accepting the higher price of children in exchange for higher potential earnings. This endogenous sorting implies that a simple comparison of outcomes between women observed in each sector would be misleading, as it conflates the sector's causal effect with the pre-existing preferences of the women who choose them.

5 Model Without Quality

In this section, we conduct a counterfactual experiment to isolate the importance of the quality-quantity (Q-Q) and time-expenditure (E-T) trade-offs. We solve a restricted version of the model where women cannot choose child quality inputs. To make the models comparable, we fix the time and expenditure inputs (h_0, h_1, e_0, e_1) to their average values from the full model simulation. This restricted framework is conceptually similar to Adda et al. (2017), which also abstracts from the quality margin.

Table 6 presents the results. Shutting down the quality margin reveals its crucial role in managing family and career.

First, without the quality dimension, women can only adjust on the quantity margin. This forces all family preferences to be expressed in terms of quantity, removing the option for a quality-quantity substitution. As a result, overall fertility increases by 19.6% (from 1.674 to 2.003).

Second, the motherhood penalty becomes substantially larger, increasing by 30.7% (from -0.420 to -0.549). By removing the Q-Q and E-T trade-offs, we eliminate the primary tools women use to buffer the career costs of children. Faced with this harsher constraint, women lean more heavily on the one timing margin they still control: fertility delay. The delay ratio (n_1/n_0) increases significantly from 1.826 to 2.762.

Third, the lack of these adjustment margins forces a starker polarization in outcomes. Fertility dispersion ($\sigma(\log(n_0|n_1))$) more than triples, rising dramatically from 0.250 to 0.810. This suggests that without the ability to use Q-Q/E-T trade-offs, it becomes hard to balance career and family, and women are pushed toward more extreme, binary choices:

a "career track" with very low fertility or a "family track" with high fertility, driving up the overall variance in outcomes.

This experiment highlights that frameworks like Adda et al. (2017) may overstate the career costs of children by not accounting for the crucial mitigation role of endogenous quality investment. More surprisingly, it shows that these Q-Q/E-T margins and the industry-choice margin are not substitutes for each other. When we shut down the quality margin, women do not flock to or from non-linear sectors (the share of women in non-linear barely moves, from 0.572 to 0.581). This suggests that the Q-Q and E-T trade-offs are the primary, most efficient margins for balancing family and career, and that industry choice is a separate decision, rather than a primary substitute for managing child-rearing costs.

	Fertility	Time	Expenditure	Quality	NL-Share	Penalty	Fert. Delay	Fert. Dispersion
	n_0+n_1	$\frac{n_0h_0+n_1h_1}{n_0+n_1}$	$\frac{n_0e_0+n_1e_1}{n_0+n_1}$	$\frac{n_0q_0+n_1q_1}{n_0+n_1}$			n_1/n_0	$\sigma(\log(n_0+n_1))$
Full Model	1.674	0.153	0.150	0.120	0.572	-0.420	1.826	0.250
Without Quality	2.003	0.162	0.109	0.101	0.581	-0.549	2.762	0.810

Table 6: Model with and Without Quality Choice

Notes: This table compares the average outcomes from the full model simulation against a restricted model where time and expenditure inputs per child (h_0, h_1, e_0, e_1) are fixed to their average values from the full model.

6 Policy Exercise

To understand how the trade-offs available to women mediate the impact of policy, we conduct a counterfactual experiment in which we exogenously reduce the price of quality-related expenditures ($\bar{w}$) by 50%. This can be interpreted as a substantial government subsidy for childcare or other child-related goods. We analyze this partial equilibrium experiment in both our full model and the restricted model without the quality margin.

The results, presented in Table 7, highlight the crucial role of the quality-quantity (Q-Q) and time-expenditure (E-T) trade-offs. In the full model, the policy leads to a modest fertility increase of 11.5 percent. The primary effect is a large increase in child quality, as women increase both their monetary expenditure (ΔExpenditure = 0.284) and, surprisingly, their time investment (ΔTime = 0.114). This suggests a strong complementarity in the production of quality: the cheaper expenditure input raises the marginal product of parental time, making it optimal to increase both. This combination of higher fertility and increased time investment results in an increasing motherhood penalty (ΔPenalty = -0.137) in line with Bover et al. (2025) who also show that policies that increase fertility reduce women's participation in the labor market and lower their lifetime earnings.

The importance of the quality margin becomes stark when we consider the model without the quality margin. Here, the policy acts as a simple per-child cash transfer. Without the ability to substitute towards quality, the entire effect is channeled into quantity, resulting in a fertility boom nearly three times larger (ΔFertility = 0.326). This large increase in fertility necessitates a much larger reallocation of time from the labor market, causing the motherhood penalty to more than double (ΔPenalty = -0.304).

This experiment demonstrates that the Q-Q and E-T trade-offs act as crucial "shock absorbers." Frameworks that do not account for these margins of adjustment will likely overestimate the fertility response to policies like childcare subsidies and, critically, also overestimate the negative consequences for women's careers.

	ΔFertility	ΔPenalty	ΔQuality	ΔTime	ΔExpenditure
Full Model	0.115	-0.137	0.222	0.114	0.284
Model Without Quality	0.326	-0.304	-	-	-

Table 7: Effect of a decline in quality cost $\bar{w}$

Notes: This table reports the change (Δ) in key outcomes from a counterfactual experiment involving a 50% decline in the price of quality-related expenditures ($\bar{w}$). The 'Full Model' includes all margins of adjustment, including the quality-quantity (Q-Q) and time-expenditure (E-T) trade-offs. The 'Model Without Quality' is a restricted simulation where time (h_t) and expenditure (e_t) inputs are fixed at their full model median values, thus shutting down these trade-off margins.

7 Conclusion

This paper analyzes the interaction between fertility, child penalties, and career choices; motherhood penalties are not an exogenous outcome but are endogenously shaped by women's strategic decisions. Our empirical analysis of Dutch administrative data provides clean evidence for this strategic behavior. We document a significant increase in the probability that women switch to "family-friendly" linear sectors in the years immediately preceding the birth of their first child.

To understand the mechanisms driving this behavior, we build and calibrate a life-cycle model in which heterogeneous women make joint decisions over fertility, time, and resources spent on children, and career paths. The model highlights that "motherhood" is not a monolith. Rather, a woman's fertility preference is expressed differently depending on her economic opportunities. Women with high productivity in the high-growth, nonlinear sectors tend to have fewer children but invest heavily in their quality, substituting away from their expensive time and towards monetary expenditure. In contrast, women with similar fertility preferences but a comparative advantage in the linear sector opt for higher quantity, leveraging their less costly time.

This reveals that the quantity-quality and time-expenditure trade-offs are the key margins through which women optimize their choices to mitigate career penalties. Our quantitative results show that the net lifetime income loss from pursuing a suboptimal career path is a modest 2.5%. This small number is not a sign of the mechanism's irrelevance; on the contrary, it is a measure of how successfully women use the flexibility of quality and time investments to minimize the costs of their joint fertility and career choices. However, we also show that in the absence of this flexibility, i.e., in a model without quality margin, fertility is 19% higher at the expense of a 30% higher motherhood penalty.

Our findings have important implications for both research and policy. They caution that direct comparisons of child penalties across groups or over time can be misleading if they do not account for these endogenous fertility and sorting decisions. For example, a decline in the observed penalty could be driven by a decline in fertility rather than an improvement in gender equality. Furthermore, accounting for the quality margin is key to understanding the ineffectiveness of family policies. Ultimately, understanding the characteristics of sectors that allow women to successfully combine family and career is crucial for addressing both the challenges of low fertility and the persistence of gender inequality in the labor market.

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A Online Appendix

A.1 Data

In the empirical analysis, we rely on Dutch administrative data maintained by Statistics Netherlands (Centraal Bureau voor de Statistiek, CBS) covering the entire Dutch population. The data includes information on individual and family characteristics and employment histories. We can follow the entire Dutch population's employment starting from 2006 with details on their employment contract such as working hours, employment sector, overtime, bonuses, and other information.

Documentation for each data file used below can be found at the embedded link. Please note that these are only available in Dutch.

Personal background information and fertility outcomes are combined using gpapersoontab, and kindoudertab. Labor market histories (including sector of employment) and income data are extracted from spolisbus and integraal persoonlijk inkomen.

A.1.1 Sample

In the estimation of the child penalties, we use a balanced sample of men and women that we can follow for up to five years before and eight years after the birth of their first child. Between calendar years 2006 and 2023, the children in our balanced sample belong to birth cohorts 2011 to 2015. For some figures, we extend our sample to an unbalanced panel, including children from birth cohorts 2009 to 2017, which does not alter our main findings but provides more power for smaller sectors. Table A.1 provides means and standard deviations of our male and female samples separately. The average age at the birth of the first child is 30 for women and 32 for men. Around 24% of men and women are university-educated, and half of each sample changes their employment sector over our observation window. In particular, 27.29% of women and 17.26% of men switch between linear and non-linear sectors. Allowing for switches within a sectorgroup, i.e., changing sector among the linear (or non-linear) sectors, this fraction increases to 53.18% for women and 57.07% for men. Using this balanced sample of men and women, we find that the relative child penalty eight years after the first child's birth is 36.7% (which increases to 37.4% in the unbalanced panel). Figure A.3 a) plots the event study results of our penalty estimation. In contrast to the results from Denmark in Kleven et al. (2019a), before birth, men and women do not exhibit parallel labor income trends. However, our results align with those of Artmann et al. (2022), who also utilize Dutch data from

1999 to 2019 and observe distinct pre-trends for men and women, particularly when considering the non-college-educated population. For college-educated men and women, a parallel trend is observed before birth, accompanied by the typical decline in earnings for women but an increase in earnings after the birth of their first child. Our sample comprises mostly non-college-educated individuals, resulting in different pre-trends overall. Still, when only college-educated men and women are considered, we find the same patterns as Artmann et al. (2022). We estimate an overall penalty of 38.7%, which is slightly lower than that reported in Artmann et al. (2022) and can be attributed to the difference in calendar years considered. Additionally, anchoring the estimates three years instead of one year before the birth of the first child also leads to parallel pre-trends and increases the penalty after eight years to 39.7%, which is comparable to the findings of Rabaté and Rellstab (2022), who also use Dutch data (for the years 1999-2016) and estimates penalties (anchored three years before birth) between four years before and seven years after the first child's birth.

A.1.2 Variable definitions

To estimate returns to employment and the riskiness of a sector, we first transform all labor income variables into full-time equivalents. To achieve this, we recover a part-time factor, determined on a job-by-job basis per pay period by Statistics Netherlands, and capture the ratio of weekly working hours to the usual full-time working hours per week as specified in collective labor agreements. Returns to employment within a sector are measured using a Mincerian regression in which we regress years of education, potential working experience (linear and quadratic terms), and calendar year fixed-effects on hourly wages. Hereby, we approximate the potential working experience of an individual by subtracting the years of education and six from the individual's age. Estimates of the potential working experience for each sector serve as the measure of returns to experience. To measure the riskiness of a sector, we first recover the year-to-year log-income growth based on individuals employed in a given sector for at least two consecutive years (irrespective of whether they were employed full-time or part-time and whether they remained continuously employed within a year). We then calculate the standard deviation of the year-to-year log income growth as a measure of riskiness. This means riskiness captures possible income fluctuations due to promotions, demotions, or discontinuous employment within a given sector. For these measures, we pool the calendar years 2014 to 2018 and include all men and women employed at some point during this time frame.

Table A.1: Estimation sample - summary statistics

	Women	Men
Age at first birth	29.86	32.18
	[4.378]	[4.988]
University education	0.2360	0.2352
	[0.4246]	[0.4241]
STEM field degree	0.0348	0.3435
	[0.1834]	[0.4749]
Years of education	18.8018	18.5837
	[2.8533]	[3.1041]
Part-time employed	0.5981	0.2639
	[0.4903]	[0.4408]
Fixed-term contract	0.3879	0.3479
	[0.4873]	[0.4763]
Always in linear sector employed	0.3605	0.1217
	[0.4801]	[0.3269]
Always in non-linear employed	0.2722	0.6325
	[0.4451]	[0.4821]
Switch between sectors (across groups)	0.2729	0.1726
	[0.4455]	[0.3779]
Switch between sectors (incl. within groups)	0.5318	0.5707
	[0.4990]	[0.4950]
Observations	499,713	973,158

NACE sector	re-grouped sector	Definition
A	A	Agriculture, Forestry and Fishing
B	B	Mining and Quarrying
C	C	Manufacturing
D	D	Electricity, Gas, Steam and Air Conditioning Supply
E		Water Supply; Sewerage, Waste Management and Remediation Activities
G		Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles
H		Transportation and Storage
F	F	Construction
I	I	Accommodation and Food Service Activities
R		Arts, Entertainment and Recreation
J	J	Information and Communication
K	K	Financial and Insurance Activities
L		Real Estate Activities
M	M	Professional, Scientific and Technical Activities
N		Administrative and Support Service Activities
O	O	Public Administration and Defence; Compulsory Social Security
P	P	Education
Q	Q	Human Health and Social Work Activities
S	S	Other Service Activities
T		Activities of Households as Employers; Undifferentiated Goods and Services Producing Activities of Households for Own Use
U		Activities of Extraterritorial Organisations and Bodies

Table A.2: Re-grouped NACE Industry Classification

A.1.3 Linear and Non-Linear Sectors

In order to determine model relevant determination of linear and non-linear sectors, we analyze several characteristics of sectors. These include total hours per year, overtime occurrence, riskiness (defined as standard deviation of income), return to employment (estimated via a Mincerain regression) for women, part-time prevalence, and whether contracts are open-ended. We define a total ranking of these 6 characteristics as the sum of individual rankings. Table A.3 below shows the value and ranking of each characteristic. A lower value in in the first four characteristics and a higher value amomg the last two characteristics indicate greater linearity or family friendliness. Hence, a lower value in the overall ranking corresponds to linear sectors coming from a composite measure. We use returns to employment for women rather than overall since women and men perform within sectors different types of occupations which we cannot obsere or control for.

Linear Sectors	Annual Hours	rank	Overtime Occurrence	rank	Returns to Emp	rank	Riskiness	rank	Open-ended Contract	rank rank	Part- -time	rank	Total Rank
P	1310	4	0.03	1	0.94	2	0.26	6	0.83	4	0.62	3	25
Q	1112	1	0.10	4	0.96	3	0.29	8	0.82	5	0.78	1	32
S	1208	2	0.08	2	1.10	5	0.46	13	0.76	10	0.66	2	37
O	1701	8	0.25	10	1.03	4	0.18	2	0.90	1	0.35	8	88
K	1703	9	0.08	3	1.86	13	0.28	7	0.74	11	0.36	9	41
Non-linear Sectors													
I	1281	3	0.10	5	1.16	7	0.43	12	0.62	12	0.64	4	42
M	1561	5	0.23	8	1.63	11	0.33	10	0.56	13	0.50	5	45
A	1693	7	0.24	9	1.21	8	0.34	11	0.76	9	0.40	7	48
F	1967	12	0.33	12	1.14	6	0.20	4	0.81	6	0.19	12	49
J	1850	11	0.13	6	1.73	12	0.23	5	0.78	7	0.28	10	49
D	1607	6	0.26	11	1.50	10	0.18	9	0.77	8	0.43	6	51
C	1837	10	0.36	13	1.44	9	0.17	3	0.86	3	0.27	11	51

Table A.3: Linear and Non-linear Sectors

A.2 Empirical Specification of penalty estimation

To estimate child penalties, we built on the framework developed by (Kleven, Landais and Søgaard, 2019a) and estimate the following regression separately by gender (g):

$$Y_{ist}^{g} = \sum_{j \neq -1} \alpha_j^g I[t = j] + \sum_k \beta_k^g I[k = age_{is}] + \sum_y \gamma_y^g I[y = s] + \nu_{ist}^g$$

where Y_{ist}^g denotes the earnings of individual i, in calendar year s, at event time t. The first term captures a full set of event time dummies, where event time $t = 0$ marks the birth of the first child. Since we exclude $t = -1$, the coefficients measure the impact of the first child relative to the year before birth. The second term controls for life-cycle and the third for time trends by including sets of dummies for the age of individual i and calendar year s, respectively. The effects of all three sets of dummies are identified by the variation in age at first childbirth after conditioning on age and year (see, Kleven, Landais and Søgaard, 2019a, for details of the method). After estimating the effect of children on men and women separately, we convert estimated level effects into percentages: $P_t^g = \frac{\hat{\alpha}_t^g}{E[\tilde{Y}_{ist}^g|t]}$ with $\tilde{Y}_{ist}^g$ capturing the predicted earnings without the contribution of the event time dummies (i.e., excluding the first term from Equation 1). We apply this transformation to interpret P_t^g as the percentage loss of average earnings that individual i of gender g experiences due to having a child at $t = 0$, i.e., to get the motherhood penalty. Additionally, we calculate a relative parenthood penalty, P_t, measuring the relative loss women compared to men experience at event time t due to children: $P_t = \frac{\hat{\alpha}_t^{md} - \hat{\alpha}_t^w}{E[\tilde{Y}_{ist}^w|t]}$.

To investigate gender differences in sector switching around the time of the first birth, we extend the framework developed by Kleven, Landais and Søgaard (2019a) and fully interact it with gender.

$$
\begin{aligned}
Y_{ist} = & \sum_{j=-5, j\neq -1}^{8} \alpha_j I[t=j] + \sum_{j=-5, j\neq -1}^{8} \alpha_j^F \left(I[t=j] * female \right) \\
& + \sum_k \beta_k I[age=k] + \sum_k \beta_k^F \left(I[age=k] * female \right) \\
& + \sum_s \gamma_s I[year=s] + \sum_s \gamma_s^F \left(I[year=s] * female \right) \\
& + \delta female + \nu_{ist}
\end{aligned}
$$

where Y_{ist} indicates whether i switched the employment sector, in calendar year s, at event time t. The coefficients of interest are the α_j^F's capturing the difference in women's vs. men's probability of switching to another sector (or to a linear sector).

In the final step, to recover differences in switching behavior among women (and men) with high and low preferences regarding the sector to which they switch, we employ a triple-interaction specification. In particular, we interact the event dummies with an indicator for having one child only (vs. more) and an indicator for being employed in a linear sector (vs. non-linear sector). We do this estimation separately for men and women.

$$
\begin{aligned}
Y_{ist} = & \sum_{j=-5, j\neq -1}^{8} \alpha_j I[t=j] + \sum_{j=-5, j\neq -1}^{8} \alpha_j^L \left(I[t=j] * linear \right) + \sum_{j=-5, j\neq -1}^{8} \alpha_j^M \left(I[t=j] * multi \right) \\
& + \sum_{j=-5, j\neq -1}^{8} \alpha_j^{FM} \left(I[t=j] * linear * multi \right) \\
& + \sum_k \beta_k I[age=k] + \sum_k \beta_k^L \left(I[age=k] * linear \right) + \sum_k \beta_k^M \left(I[age=k] * multi \right) \\
& + \sum_k \left(\delta_k^A I[age=k] * linear * multi \right) \\
& + \sum_s \gamma_s I[year=s] + \sum_s \gamma_s^L \left(I[year=s] * linear \right) + \sum_s \gamma_s^M \left(I[year=s] * multi \right) \\
& + \sum_s \left(\gamma_s I[year=s] * linear * multi \right) \\
& + \delta^L linear + \delta^M multi + \delta^{LM} linear * multi + \nu_{ist}
\end{aligned}
$$

where Y_{ist} indicates whether i switched the employment sector, in calendar year s, at event time t, $linear$ is an indicator taking the value one if the employment sector is a linear sector, and $multi$ is an indicator capturing whether an individual as multiple children (at the end of the observation period) or a single child. The coefficients of interest are the α_j^{LM}'s, which capture the differential switching probability of mothers who have one vs. more than one child at the, and whether these mothers switch to a linear or a non-linear sector.

For both extensions, to scale the effects and differences, we convert the coefficients into percentage changes due to the arrival of the first child. We employ the percentage loss conversion as in the conventional child penalty estimation by comparing the coefficients (here α_F or α^{LM}) to the predicted outcome (here switch probability), in the absence of the first child.

It is important to note here that switching behavior, as opposed to the evolution of earnings (around birth), is an endogenous decision, for which causal identification in a reduced form is challenging. In the empirical section, we are interested in documenting how switch probabilities around the birth of the first child differ by gender (Figure 5) and within gender by fertility preferences (Figure 6), net of any life cycle and time trends.

A.3 Additional Tables

Dependent Variable: Number of children				
Linear	0.026*	0.039***	0.034**	0.042***
	(0.082)	(0.008)	(0.022)	(0.005)
HH Income Quantile	0.038***		0.049***	0.053***
	(0.000)		(0.000)	(0.000)
Work Hours	-0.007***	-0.006***	-0.006***	
	(0.000)	(0.000)	(0.000)	
Income Quantile		-0.011*	-0.025***	-0.051***
		(0.076)	(0.000)	(0.000)
Country fixed effects	Yes	Yes	Yes	Yes
N	7204	7204	7204	7204
R2	0.076	0.074	0.078	0.067

Table A.4: Fertility in Linear Sectors

Notes: Data is from Harmonized European Time-Use Survey, wave 2010. Countries are the UK, France, and Germany. All regressions include controls for age and education.

Dependent Variable: Childcare per child				
Linear	3.839**	1.803	2.606*	3.490**
	(0.011)	(0.239)	(0.087)	(0.024)
HH Income Quantile	-6.280***		-7.943***	-7.556***
	(0.000)		(0.000)	(0.000)
Work Hours	-0.595***	-0.716***	-0.742***	
	(0.000)	(0.000)	(0.000)	
Income Quantile		1.387**	3.656***	0.662
		(0.036)	(0.000)	(0.301)
Country fixed effects	Yes	Yes	Yes	Yes
N	7204	7204	7204	7204
R2	0.184	0.178	0.188	0.174

Table A.5: Childcare Time per Child

Notes: Data is from Harmonized European Time-Use Survey, wave 2010. Countries are the UK, France, and Germany. All regressions include controls for age, education, and the number of children. Young children are between the ages of 0 and 7, and older children are between the ages of 7 and 17.

	All Children	All Care Young Children	Older Children	Quality Care All Children	Basic Care All Children
Linear	5.134**	11.665***	-1.021	2.199**	2.935*
	(0.011)	(0.003)	(0.517)	(0.032)	(0.069)
HH Income Quantile	-6.773***	2.990	-5.998***	-2.598***	-4.175***
	(0.000)	(0.167)	(0.000)	(0.000)	(0.000)
Work Hours	-0.941***	-1.544***	-0.252***	-0.279***	-0.661***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Country fixed effects	Yes	Yes	Yes	Yes	Yes
N	7204	2875	4329	7204	7204
R2	0.183	0.084	0.073	0.062	0.169

Table A.6: Total Childcare Time

Notes: Data is from Harmonized European Time-Use Survey, wave 2010. Countries are the UK, France, and Germany. All regressions include controls for age, education, and the number of children. Young children are between the ages of 0 and 7, and older children are between the ages of 7 and 17.

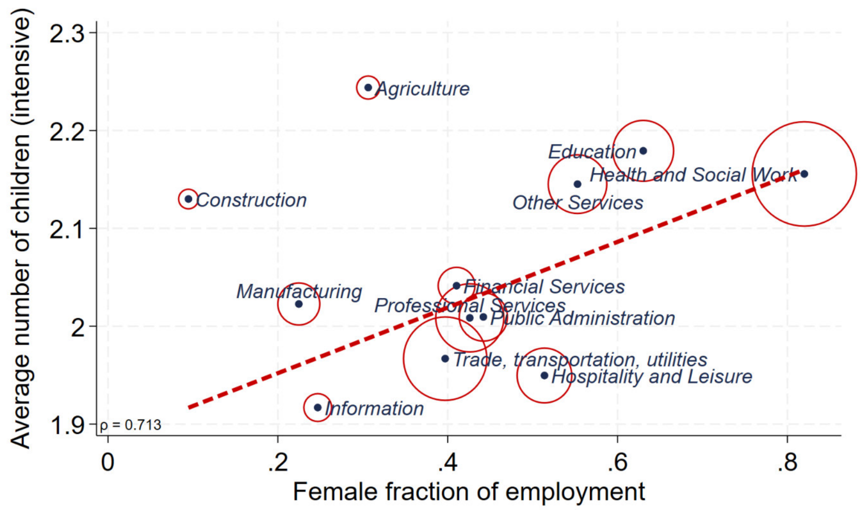
	All Children	All Care per child Young Children	Older Children
Linear	2.581***	7.311**	0.508
	[0.505]	[3.568]	[2.022]
HH Income	-0.000**	0.000	-0.000
	[0.000]	[0.001]	[0.000]
Work Hours	-0.079***	0.109	-0.055
	[0.013]	[0.117]	[0.063]
Observations	3213	341	1112
R-squared	0.120	0.123	0.046

Table A.7: Time with Children (Netherlands)

Notes: Data is from the LISS household survey conducted in the Netherlands. All regressions include controls for age, education, and the number of children. Young children are those not yet attending primary school, and older children are those attending primary school.

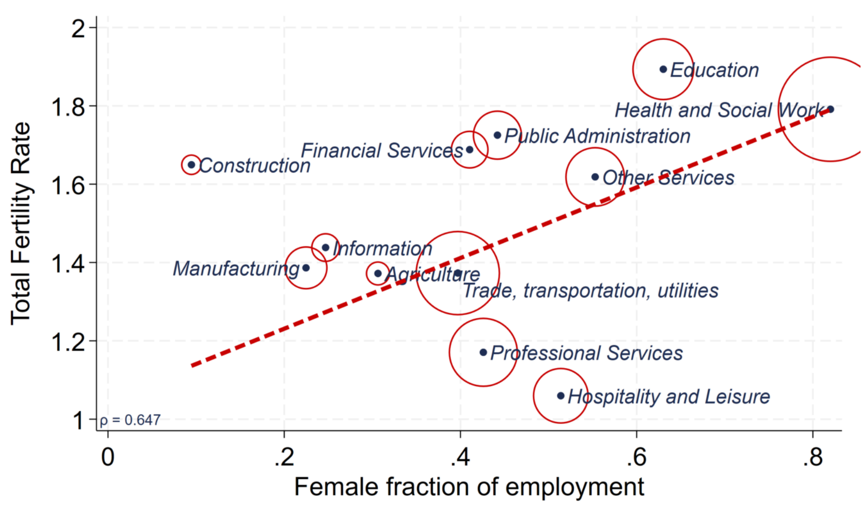
A.4 Additional Figures

Figure A.1: Intensive Fertility and Female Share across Sectors



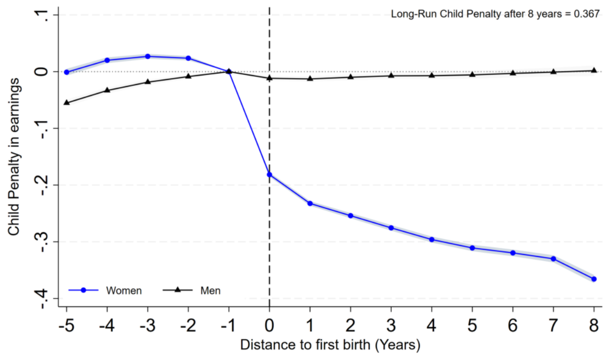
Notes: The figure plots the sector-level employment share of women and the total number of children (by the end of 2023), only among mothers. We also report the weighted correlation coefficient by the sector size within female employment.

Figure A.2: Total Fertility Rate and Female Share across Sectors

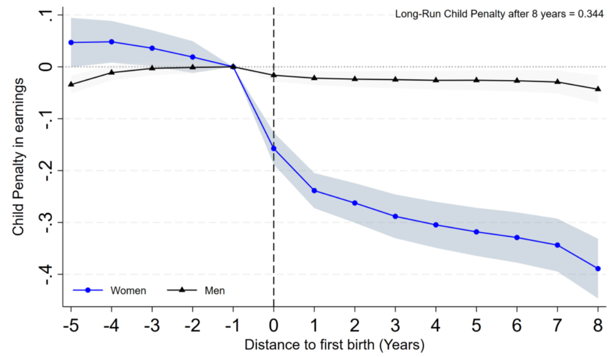


Notes: The figure plots the sector-level employment share of women and the total fertility rate. We also report the weighted correlation coefficient by the sector size within female employment.

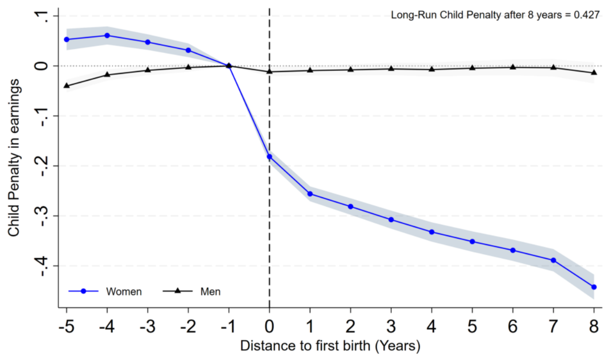
Figure A.3: Child penalties by sector of employment



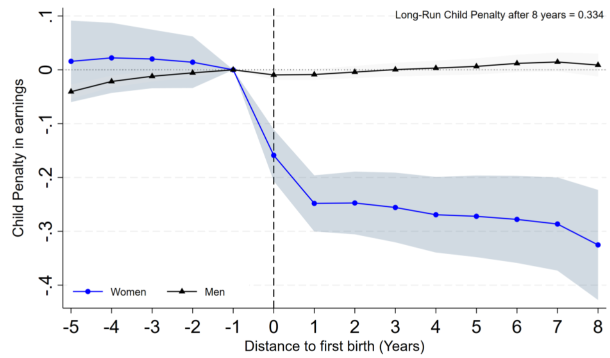
(a) Any sector of employment



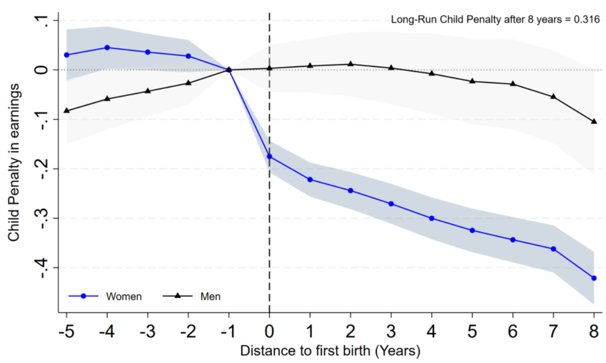
(b) Manufacturing



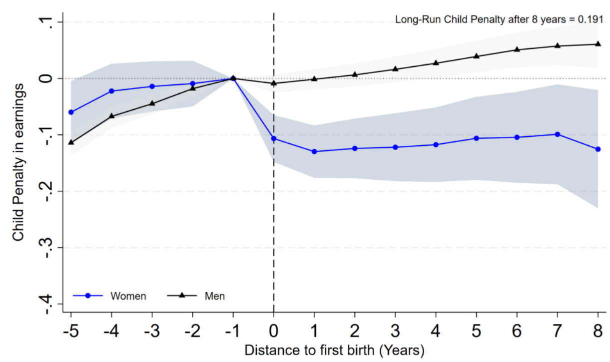
(c) Electricity, Wholesale, Transportation



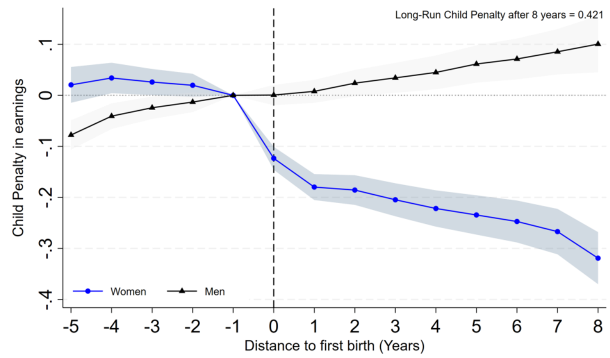
(d) Construction



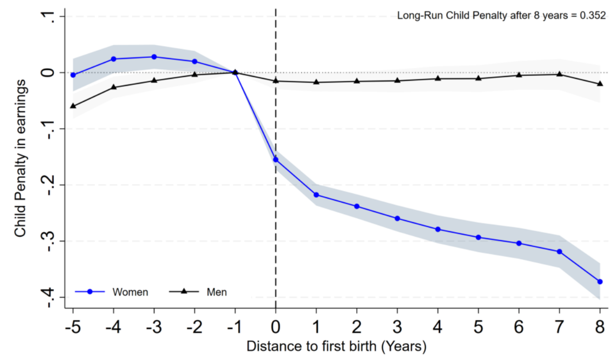
(e) Arts, Accommodation, Food service



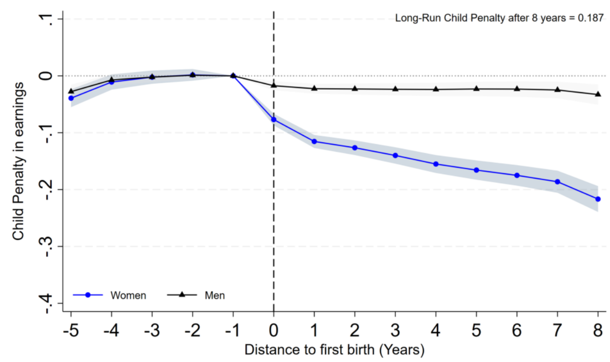
(f) Information and communication



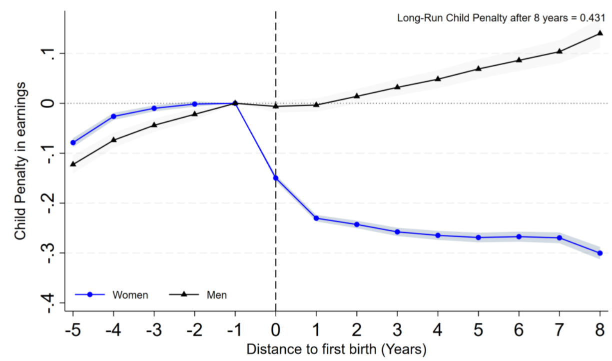
(g) Financial, insurance, real estate activities



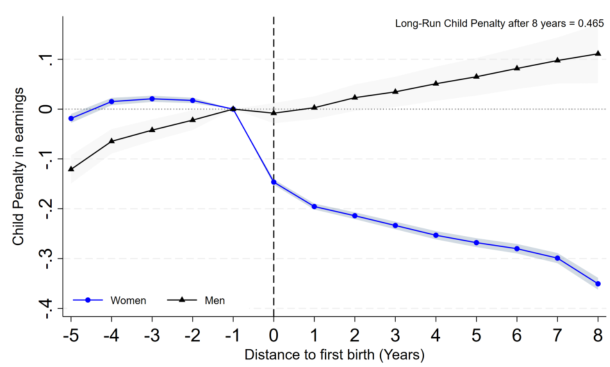
(h) Professional, scientific, technical, administrative activities



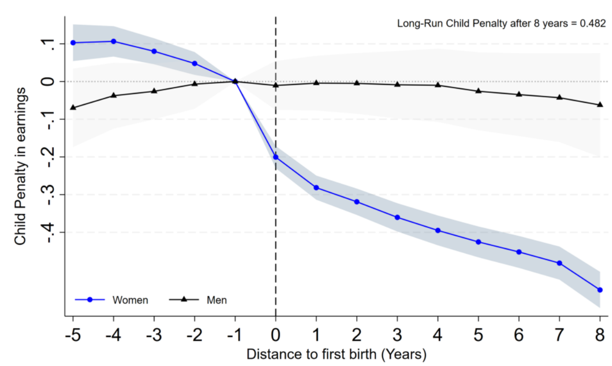
(i) Public administration



(j) Education



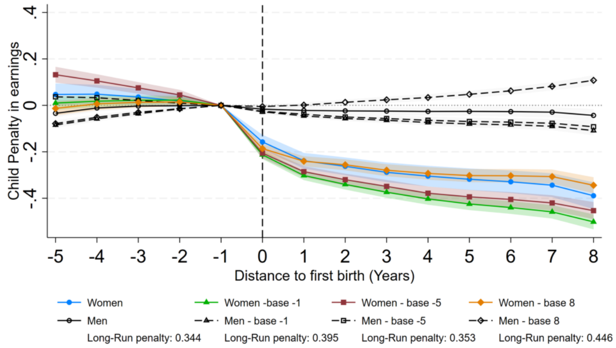
(k) Health and social work



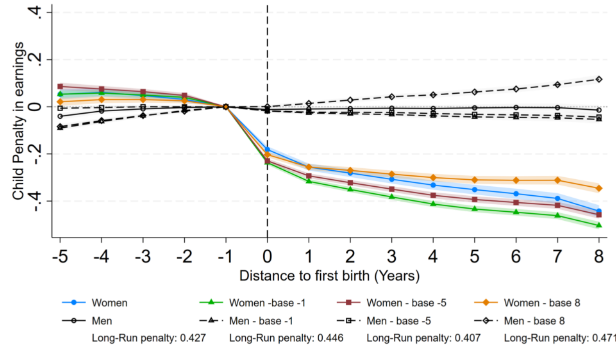
(l) Other

Notes: Each panel shows the evolution of mothers' (blue dots) and fathers' (black triangles) total labour income from 5 years before and to 8 years after the birth of their first child. Each panel considers a different employment sector, in which the mothers/fathers were employed between 5 years before and 8 years after the birth of their first child. Event time 0 marks the birth of the first child. The long-run child penalty that women face after 8 years (i.e., the relative loss women experience compared to men) is reported in the top right corner of each sub-graph. The value at t = -1 is normalized to zero so that coefficients measure the impact of the first child relative to the year before birth. The shaded areas indicate the 95 percent confidence interval.

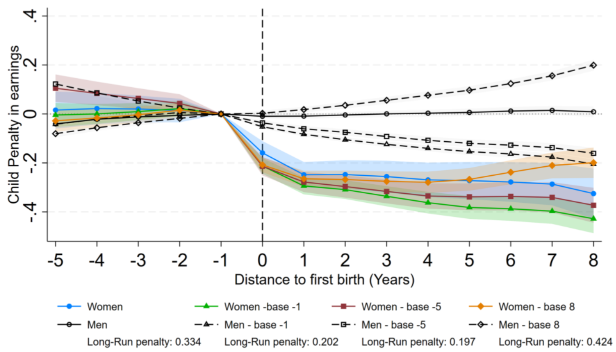
Figure A.4: Child penalties by sector of employment depending on timing



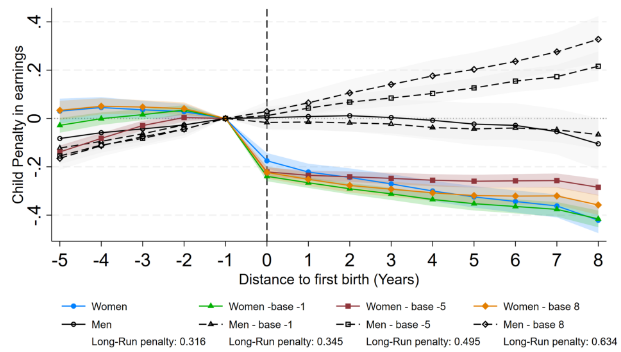
(a) Manufacturing



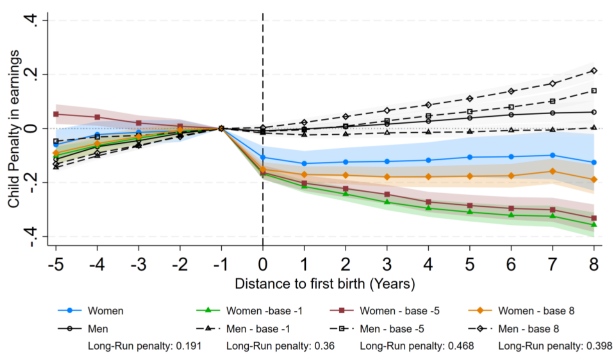
(b) Electricity, Wholesale, Transportation



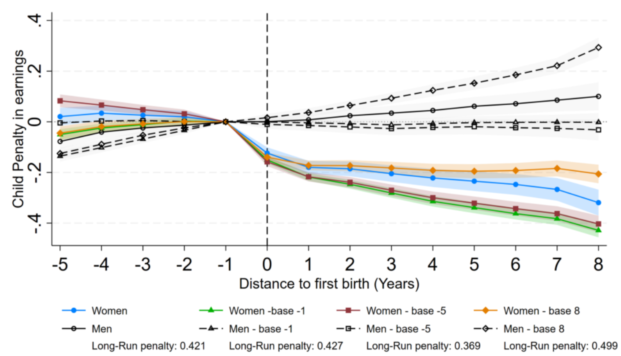
(c) Construction



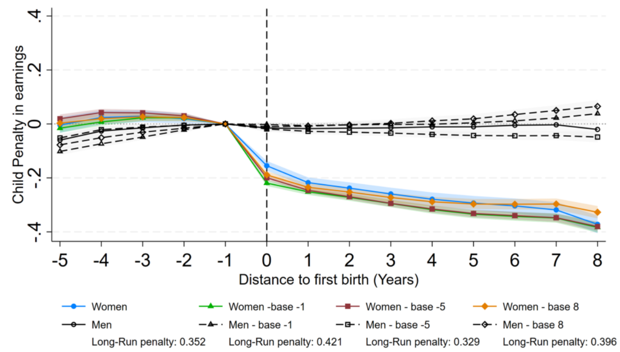
(d) Arts, Accommodation, Food service



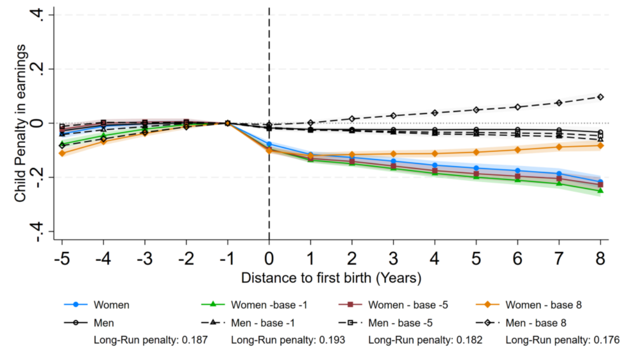
(e) Information and communication



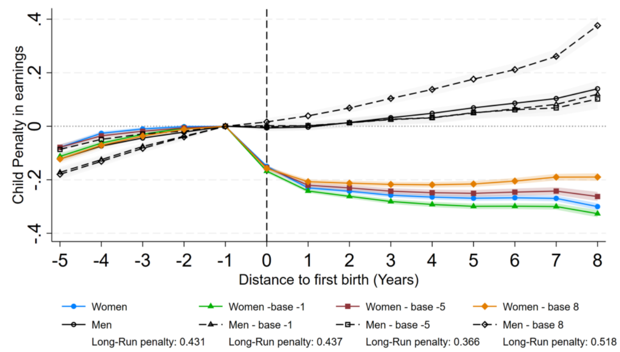
(f) Financial, insurance, real estate activities



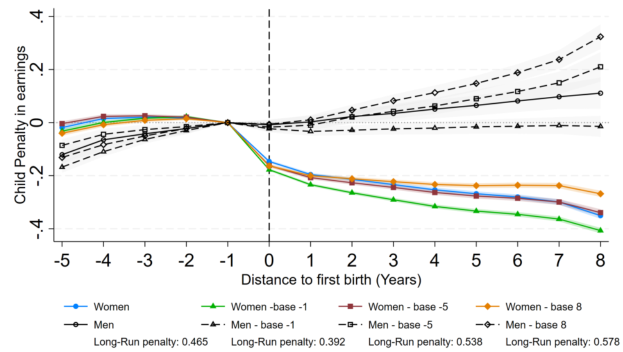
(g) Professional, scientific, technical, administrative activities



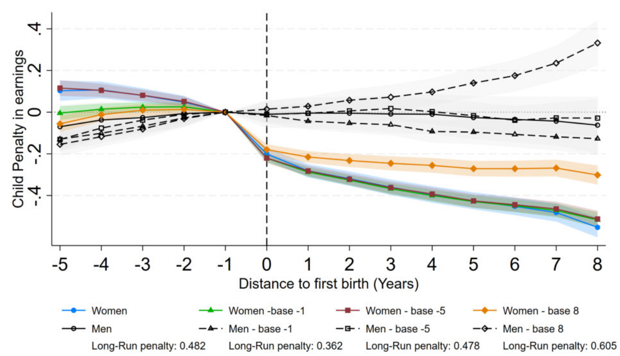
(h) Public administration



(i) Education



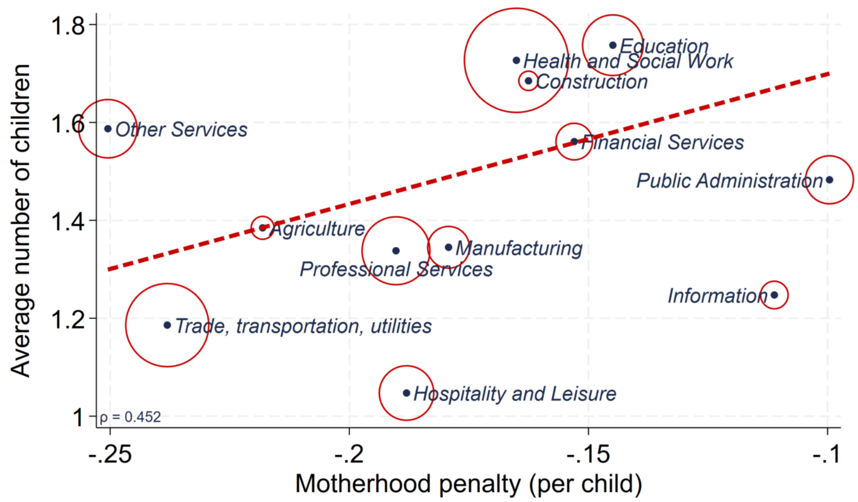
(j) Health and social work



(k) Other

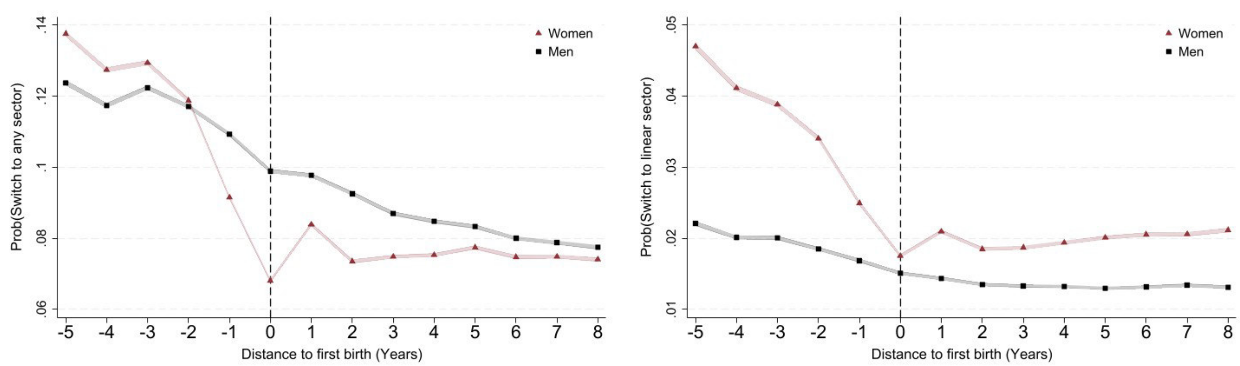
Notes: Each panel shows the evolution of mothers' (blue, green, red) and fathers' (black and gray) total labour income from 5 years before and to 8 years after the birth of their first child. Each panel considers a different employment sector, in which the mothers/fathers were employed between 5 years before and 8 years after the birth of their first child. The baseline timing of sector choice is distinguished between, the sector one year prior to the birth (squares), the sector eight years after the birth (diamonds), and the same sector throughout the entire time (circles). Event time 0 marks the birth of the first child. The long-run child penalty that women face after 8 years (i.e., the relative loss women experience compared to men) is reported at the bottom of each sub-graph. The value at t = -1 is normalized to zero so that coefficients measure the impact of the first child relative to the year before birth. The shaded areas indicate the 95 percent confidence interval.

Figure A.5: Per-Child Motherhood Penalty and Fertility



Notes: The figure plots the sector-level motherhood penalty per child and the total number of children (by the end of 2023) including the childless, i.e., the intensive margin. We also report the weighted correlation coefficient by the sector size within female employment.

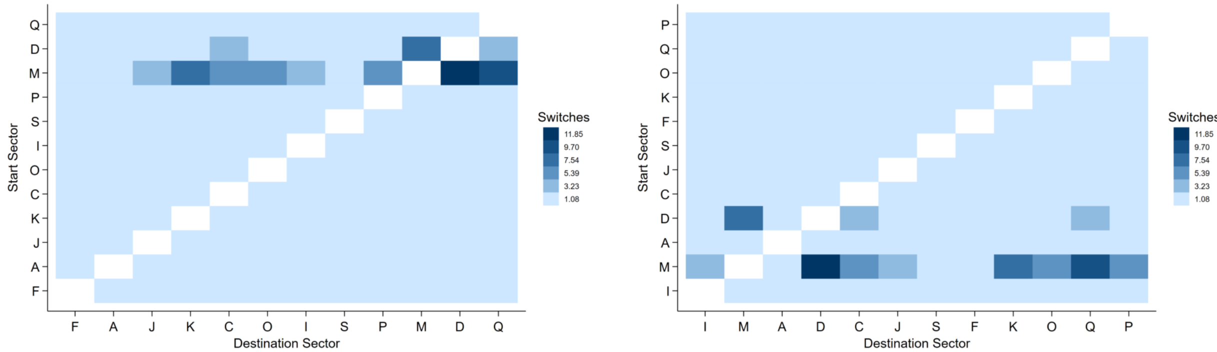
Figure A.6: Sector Switching around Birth



(a) Probability to switch any sector (means) (b) Probability to switch to linear sector (means)

Notes: The graphs plot the average switch probabilities around the time of the first birth separately for women (red triangles) and men (black squares). In panel (a), the switch to any sector, and in panel (b), the switch to a linear sector is considered. See Appendix Table A.3 for the definition of linear sectors.

Figure A.7: Sector Switching before Birth

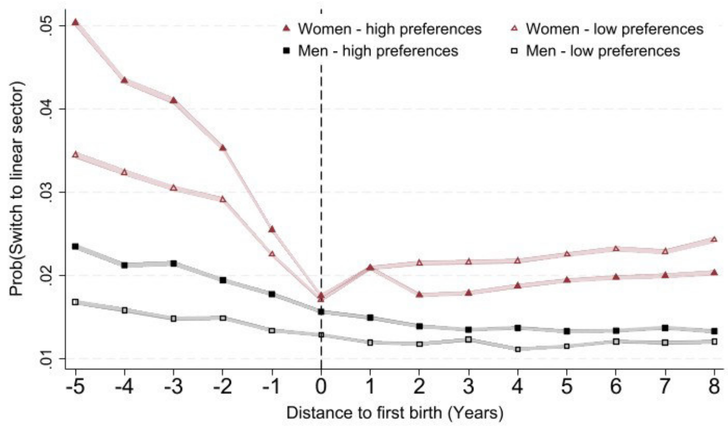


(a) Ordered by sector size

(b) Ordered by Total Fertility Rate

Notes: The graphs plot the switching intensities across all sectors. We reweight the fractions by the number of women in the starting sector. Darker colors indicate higher switching intensities.

Figure A.8: Sector Switching around Birth by fertility preference



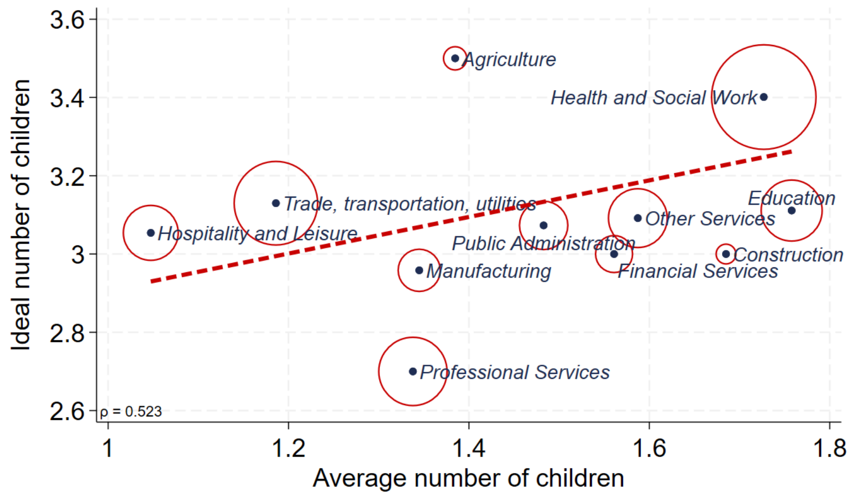
Notes: The graphs plot the average switch probabilities around the time of the first birth separately for women (red triangles) and men (black squares). The solid symbols capture Women and Men with high fertility preferences (measured by their final number of children in 2023 being above one), and the hollow symbols capture women and men with low fertility preferences (measured by them having a single child in 2023). See Appendix Table A.3 for the definition of linear sectors.

A.5 Model Results

A.5.1 Model Simulation

To simulate the model, we generate a large number of women who are heterogeneous with respect to linear and non-linear sector productivites (z_l and z_n) and fertility preference (γ). We draw these three random variables from a jointly normal distribution $\mathcal{N}(M, \Sigma)$, where

Figure A.9: Fertility and desired fertility



Note: The figure presents, on the employment sector level, the average number of children on the x-axis and the desired number of children on the y-axis. We report the weighted correlation coefficient by the sector size within female employment. The desired number of children is based on the answer to the survey question: "Can you to tell us how many children you would ideally desire? If you already have children, we would still like to know how many children you would ideally like to have. The children can be born to you or adopted." Both measures consider employed women between ages 20 and 50.

$$M = [\log(\bar{z}_l) \; \log(\bar{z}_n) \; \log(\bar{\gamma})]$$

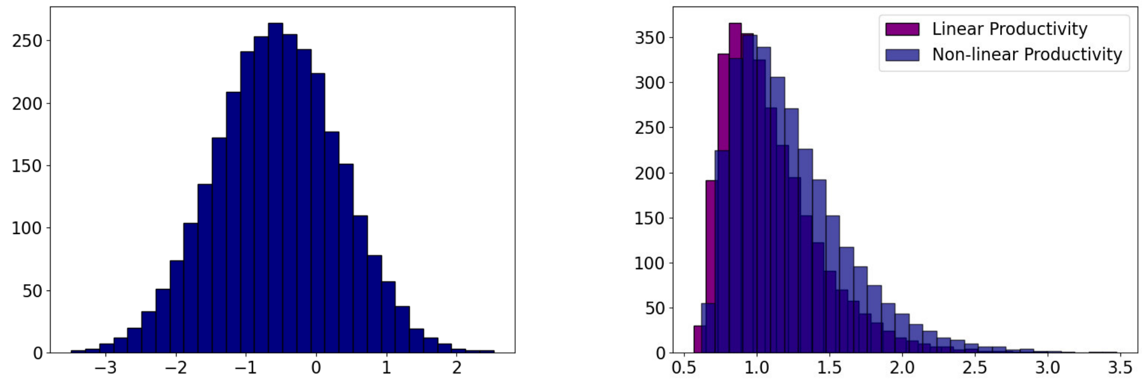
is the mean, and $\Sigma = \Lambda C \Lambda'$ is the variance covariance matrix, Λ is the vector of standard deviations, and C is the covariance matrix.

$$\Lambda = [\sigma_{z_l} \, \sigma_{z_n} \, \sigma_\gamma]$$

$$C = \begin{bmatrix} 1 & \sigma_2 & \sigma_0 \\ \sigma_2 & 1 & \sigma_1 \\ \sigma_0 & \sigma_1 & 1 \end{bmatrix}$$

We use a Sobol sequence to generate quasi-random numbers from the above distribution. Sobol sequence allows for a more evenly distributed numbers close to population moments. Figure A.10 plots histograms of the random sample used.

Figure A.11 plots the simulated total fertility distribution in our model.



(a) Fertility Preference ($\log(\gamma)$)

(b) Productivities (z_l and z_n)

Figure A.10: Fertility and Productivity distribution

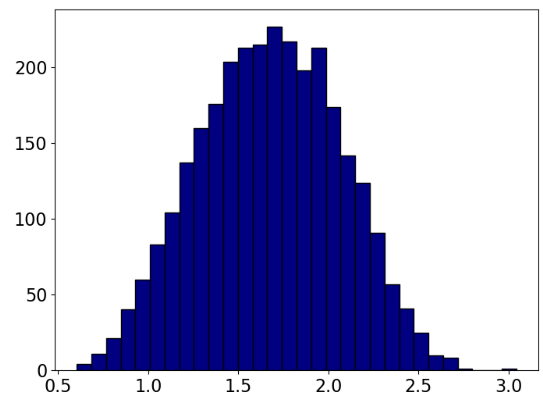
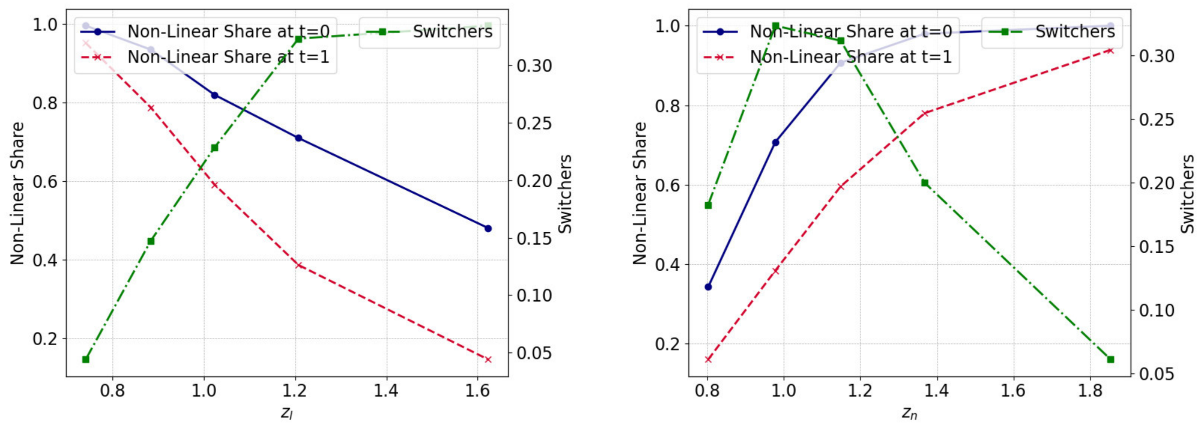


Figure A.11: Fertility Distribution

A.5.2 Industry Choice and Productivity

The model highlights how career paths are shaped by sector-specific productivities. Figure A.12 decomposes these choices. As expected, women sort according to their comparative advantage: a higher linear productivity (z_l) increases the share of women in the linear sector, while a higher non-linear productivity (z_n) increases the share in the non-linear sector (Figure A.12a and A.12b).

The characteristics of the "switcher", a woman who moves from the non-linear to the linear sector, are more complex. The probability of switching increases monotonically with linear productivity (z_l), indicating that a strong outside option in the linear sector



(a) By Linear Sector Productivity (z_l) (b) By Non-Linear Sector Productivity (z_n)

Figure A.12: Industry Choice and Productivity

is a prerequisite for this strategy. However, the relationship with non-linear productivity (z_n) follows an inverted U-shape. The propensity to switch is highest for women with moderately high, but not exceptionally high, non-linear productivity. Women with a very strong comparative advantage in the non-linear sector find it optimal to remain there, even if they have a high taste for fertility.

The model therefore identifies the switcher as a specific type of woman: one who is highly productive in the flexible linear sector but only moderately so in the high-growth non-linear sector. This makes her willing to "cash in" on her early-career experience accumulation in the non-linear sector by moving to a more family-friendly job to have children.

A.5.3 Model Equations

This section presents the full set of model equations and first-order conditions. The household maximizes lifetime utility by choosing consumption (c_t), savings (b), and the quantity (n_t) and quality (q_t) of children in each of two periods. Child quality is produced using time (h_t) and monetary expenditures (e_t).

Household Problem:

$$\max_{c_0,c_1,b,n_0,n_1,q_0,q_1,e_0,e_1,h_0,h_1} V = \log(c_0) + \gamma_i \frac{(\alpha n_0^\rho + (1-\alpha) q_0^\rho)^{\frac{1-\eta}{\rho}}}{1-\eta} + \beta \left(\log(c_1) + \gamma_i \gamma_f \frac{(\alpha n_1^\rho + (1-\alpha) q_1^\rho)^{\frac{1-\eta}{\rho}}}{1-\eta} \right)$$

Budget Constraints:

$$\begin{aligned} c_0 + \bar{w}(e_0 + \bar{e})n_0 + b &= w_0 l_0 \\ c_1 + \bar{w}\left(e_1 + \bar{e}\right)n_1 &= w_1 l_1 + bR \end{aligned}$$

Quality Production:

$$q_t = \left(\omega h_t^{1-\sigma} + (1-\omega)e_t^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$$

Wage Equations:

$$\begin{aligned} &w_0 = z_0 l_0^{\mu_j} \\ &w_1 = z_1 \left(g z_0 l_0\right)^{\mu_j} \left(l_1\right)^{\mu_k} \quad \text{where } j, k \in \{l, n\} \end{aligned}$$

Time Allocation:

$$\begin{aligned} l_0 &= 1 - h_0 n_0 - \tau n_0 \\ l_1 &= 1 - h_1 n_1 - \tau n_1 \end{aligned}$$

First-Order Conditions

The first-order conditions with respect to the 11 choice variables are given below. Let λ_t be the Lagrange multiplier on the budget constraint and ξ_t be the multiplier on the quality production function.

$$\begin{aligned} \frac{1}{c_0} &= \lambda_0 \\ \frac{\beta}{c_1} &= \lambda_1 \\ \lambda_0 &= R\lambda_1 \\ \gamma_i U_{n,0} - \lambda_0 \bar{w}\left(\bar{e} + e_0\right) + \lambda_0 \frac{\partial(w_0 l_0)}{\partial n_0} + \lambda_1 \frac{\partial(w_1 l_1)}{\partial n_0} &= 0 \\ \beta\gamma_i\gamma_f U_{n,1} - \lambda_1 \bar{w}\left(\bar{e} + e_1\right) + \lambda_1 \frac{\partial(w_1 l_1)}{\partial n_1} &= 0 \end{aligned}$$

$$
\begin{aligned}
\gamma_i U_{q,0} &= \xi_0 \\
\beta\gamma_i\gamma_f U_{q,1} &= \xi_1 \\
\xi_0 \frac{\partial q_0}{\partial e_0} &= \lambda_0 \bar{w} n_0 \\
\xi_1 \frac{\partial q_1}{\partial e_1} &= \lambda_1 \bar{w} n_1 \\
\xi_0 \frac{\partial q_0}{\partial h_0} + \lambda_0 \frac{\partial (w_0 l_0)}{\partial h_0} + \lambda_1 \frac{\partial (w_1 l_1)}{\partial h_0} &= 0 \\
\xi_1 \frac{\partial q_1}{\partial h_1} + \lambda_1 \frac{\partial (w_1 l_1)}{\partial h_1} &= 0
\end{aligned}
$$

where $U_{n,t}$ and $U_{q,t}$ are the marginal utilities from the CES aggregator. The partial derivatives are:

$$
\begin{aligned}
\frac{\partial w_0}{\partial n_0} &= -(h_0+\tau)\mu_j z_0 (l_0)^{\mu_j - 1} & \frac{\partial w_0}{\partial h_0} &= -n_0 \mu_j z_0 (l_0)^{\mu_j - 1} \\
\frac{\partial w_1}{\partial n_0} &= -(h_0+\tau)\mu_j \left(g z_0\right)^{\mu_j} z_1 \left(l_0\right)^{\mu_j - 1} \left(l_1\right)^{\mu_k} & \frac{\partial w_1}{\partial h_0} &= -n_0 \mu_j \left(g z_0\right)^{\mu_j} z_1 \left(l_0\right)^{\mu_j - 1} \left(l_1\right)^{\mu_k} \\
\frac{\partial w_1}{\partial n_1} &= -(h_1+\tau)\mu_k \left(g z_0 l_0\right)^{\mu_j} z_1 (l_1)^{\mu_k - 1} & \frac{\partial w_1}{\partial h_1} &= -n_1 \mu_k \left(g z_0 l_0\right)^{\mu_j} z_1 (l_1)^{\mu_k - 1}
\end{aligned}
$$

$$
\frac{\partial q_t}{\partial e_t} = (1-\omega) q_t^{\sigma} e_t^{-\sigma} \qquad\qquad \frac{\partial q_t}{\partial h_t} = \omega q_t^{\sigma} h_t^{-\sigma}
$$

To solve the model, we reduce the system of equations. We substitute the FOCs for c_t and q_t into the remaining seven FOCs (for b, n_t, e_t, h_t). These seven equations, combined with the two budget constraints and two quality production functions, form a system of 11 equations and 11 unknowns ($b, n_0, n_1, h_0, h_1, e_0, e_1, c_0, c_1, q_0, q_1$) that we solve numerically.