Childbirth and Firm Performance: Evidence from Norwegian Entrepreneurs*

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Abstract

Using multiple administrative data sources from Norway, we examine how firm performance changes after entrepreneurs become parents. Female-owned businesses experience a substantial decline in profits, steadily decreasing to 30% below baseline ten years post-childbirth. In contrast, male-owned businesses show no decline, often growing in revenues and costs after childbirth. The profit decline for female-owned firms is most pronounced among highly capable entrepreneurs, women who are majority owners, and those with working spouses. Entrepreneurial effort is key to performance, and our findings suggest that time demands from childbirth and childcare are a significant determinant of the decline in firm profits.

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1 Introduction

An extensive body of work has shown that motherhood is associated with large declines in women's employment rates, working hours, and wages—a phenomenon known as the "child penalty" (Correll, Benard and Paik, 2007; Adda, Dustmann and Stevens, 2017; Kleven, Landais and Søgaard, 2019). Explanations include the cost of child-bearing and child-rearing (which may affect worker productivity), statistical discrimination by employers (which may lead them not to hire or promote mothers), and traditional gender norms (which lead to an unequal distribution of home production responsibilities). The literature focuses on documenting the child penalty for workers. In this paper, we use administrative data from Norway to measure the child penalty for entrepreneurs and their businesses.

We study the effect of motherhood and fatherhood on the business outcomes of private limited-liability companies after the first childbirth event. We find a substantial and persistent penalty in the profits of firms owned by a woman after she has her first child, with a steady decline to 30% ten years later. The penalty for businesses owned by a men who as his first child is close to zero and statistically insignificant.

We use rich administrative data for Norway, which allow us to precisely measure how parenthood affects the performance of firms owned by women compared to firms owned by men. The data cover the universe of private businesses for a long time period, spanning 2001 to 2018. For each business, we observe traditional balance sheet items (profits, revenues, costs, etc.) as well as other characteristics not usually included in balance sheets (such as detailed industry classification, overall employment, and the identity of the shareholders); crucially, we also observe—from population registries—the demographic characteristics of the firm's owner, including whether he/she experiences a childbirth event during the sample period. Building on recent advances in the literature on event studies (Callaway and Sant'Anna, 2021; Baker, Larcker and Wang, 2022), we estimate the child penalty by comparing firms owned by entrepreneurs who become first-time parents during our sample period with firms owned by entrepreneurs who share similar demographics (gender) and firm characteristics (year of foundation and industry) but do not become parents during our sample period.

Our main finding is that motherhood induces a large and persistent negative effect on the entrepreneur's business performance, as measured by the operating profits before owners' pay. Ten years after childbirth, firm profits of female-led businesses are 30% lower than at baseline. We find no statistically significant child penalty for male entrepreneurs. However, these different average responses mask some interesting compositional differences. In particular, male entrepreneurs grow their firms (as measured by concurrent increases in costs and revenues) following childbirth, while female entrepreneurs experience downsizing (both costs and revenues decline). Consistent with this result, we find that employment increases at male-led firms but not at female-led firms. Finally, we find that female entrepreneurs are more likely, following childbirth, to sell their firm, compared to male entrepreneurs who also experience childbirth and to entrepreneurs with similar observable characteristics who do not experience childbirth during our sample period.

While a variety of explanations have been proposed to rationalize the decline in labor earnings after childbirth, it is harder to reconcile such explanations with changes in firm performance within the context of firms facing perfect labor markets (Benjamin, 1992). In principle, changes in the entrepreneur's labor supply could lead to greater demand for external labor but that should not *per se* influence profits—as long as entrepreneurs can hire managers that are perfect substitutes for their own work within the firm. The existence of a child penalty suggests that an entrepreneur is vital to the success of her business and that hired labor is only a poor substitute for the type of labor services she brings onto the firm. Consistent with the key role of the entrepreneur/founder within a firm, we find that the child penalty increases with the entrepreneur's talent, where talent is measured by systematically abnormal firm performance in the pre-childbirth years.

An alternative explanation is the presence of a customer-based form of statistical discrimination.[1] Some customer, client or supplier relationships may be highly personal, and may be severed when there is a perception that the entrepreneur can no longer work regularly because of the demand imposed by child-rearing. Entrepreneurs are an interesting group to study because employer-based statistical discrimination—a traditional explanation for the child penalty (Correll, Benard and Paik, 2007; Becker, Fernandes and Weichselbaumer, 2019)—is not relevant in their case, as they are effectively "their own employers." Finally, it is possible that childbirth may be the symptom rather than the cause of a decline in business performance. For example, women may decide to have a child because they anticipate their business declining. In the final part of the paper, we discuss the relevance of these different

[1]For (aspiring) wage workers, statistical discrimination toward mothers has been detected in audit studies of hiring processes in multiple settings (Correll, Benard and Paik, 2007; Becker, Fernandes and Weichselbaumer, 2019).

economic mechanisms.

Our paper contributes to three strands of literature. While most prior research documents the existence of child penalties among employees, little is known about whether such penalties extend to entrepreneurs and their firms. The exception, to our knowledge, is Rutigliano (2025), a contemporaneous study using Canadian administrative data. The paper examines how childbirth affects entry into entrepreneurship, and the outcome of entrepreneurs and firms during the first 5 years after childbirth, emphasizing the importance of frictions, such as gender norms and access to informal childcare. In contrast, our paper strictly focuses on the effect on existing firms, tracking them for 10 years after childbirth. We primarily study the role of entrepreneurial skill and effort, leveraging complementary survey data on hours worked. Norway offers an especially interesting setting for this analysis, because the frictions that Rutigliano (2025) studies in Canada are substantially less relevant in our setting. Norway is one of the most gender-progressive countries in the world, with universal and subsidized childcare available to children over the age of one (Drange and Telle, 2018).[2] Yet, both papers estimate similarly large declines in women's firm profits after childbirth, suggesting that short-term policy solutions are unlikely to mitigate this phenomenon significantly.

By examining the differential impact of fatherhood and motherhood on firm performance, we shed light on the possible determinants of the gender gaps observed in entrepreneurial activity and performance. The existing literature has documented significant gender gaps in productivity and return to capital within the context of microfinance evaluations in developing countries (De Mel, McKenzie and Woodruff, 2009; Bernhardt et al., 2019). In both developed and developing countries, women face substantial barriers to entrepreneurship and access to capital (Chiplunkar and Goldberg, 2024; Morazzoni and Sy, 2022). What is less known or understood is how and to what extent parenthood affects these gaps.

Finally, our paper is related to the literature that tries to understand the distinctive role

[2] In the most recent year of data, Norway ranks as second more gender-equal country in the world (after Denmark) in the United Nations' Gender Inequality Index, while Canada ranks eighteenth (UNDP, 2025). Norwegians hold very progressive gender views: in the Gender Social Norms Index, fewer Norwegians reported gender-biased attitudes in 2007 than respondents in Canada in 2020 (UNDP, 2023), yet the lack of overlap in wave timing prevents a more direct comparison. According to the OECD Family Database, Norway has one of the world's highest public expenditures on childcare (OECD, 2025). As a result, enrollment in early childhood and care services is very high among Norwegian children: 59.2% between ages 0 and 2, and 97.3% between ages 3 and 5. No exactly comparable data are available for Canada, but Statistics Canada indicates that a little over one half of all Canadian children under the age of 6 attend child care (Statistics Canada, 2023).

of the entrepreneur (or other key executives) in explaining firm performance, with recent contributions using exogenous shocks such as the entrepreneur's death or incapacitation (Becker and Hvide, 2022; Sauvagnat and Schivardi, 2023; Bennedsen, Perez-Gonzalez and Wolfenzon, 2020; Smith et al., 2019). We look at episodes (childbirth) that are more temporary than those examined in previous literature, which may shed light on the importance of shock persistence for explaining the link between the characteristics of the entrepreneur and their businesses' performance. Recent evidence from Denmark indicates that firm performance is not influenced by whether an *employee* experiences childbirth and takes parental leave (Brenøe et al., 2024). However, given the unique role of the entrepreneur in the success of a firm, we may expect substantially different effects when the business owner experiences childbirth.

The rest of the paper is organized as follows. After describing the data (Section 2), we detail our empirical strategy for estimating the child penalty (Section 3). We then present the results (Section 4) and conclude with a discussion of the findings, complemented by evidence from survey data, and their implications (Section 5).

2 Setting and Data

We begin by introducing the Norwegian institutional setting, and then describe our administrative data.

2.1 Institutional Setting

Norway provides a favorable environment for potential entrepreneurs. Individuals seeking to start a business must only register their company with the tax authority. For an individual starting a limited liability company (*aksjeselskap*), the only substantive requirement for registration is that the firm has at least 30,000 NOK (approximately US$3,700 in 2015) in capital at the time of registration.[3] These requirements are considered minimal: in 2019, the World Bank placed Norway 9th out of 190 countries on its "Ease of Doing Business" ranking (World Bank, 2019), closely following the United States, which was ranked 7th. Women nonetheless make up only a quarter of Norwegian entrepreneurs despite making up around half of the Norwegian workforce. The presence of children is positively correlated with the

[3]Prior to 2012, this amount was 100,000 NOK (US$12,200). See Bacher et al. (2024).

probability that a woman is self-employed or runs her own business (Rønsen, 2014; Raknerud and Rønsen, 2014).

Norway is also characterized by generous support for new parents.[4] Starting at the age of one, children have access to highly subsidized public childcare. Despite these policies, Andresen and Nix (2022) have shown that Norwegian mothers experience a child "penalty" after having children, which they attribute primarily to maternal preferences for child care and gender norms.

2.2 Data

Our analysis is based on several administrative registers maintained by Statistics Norway that we can link through identifiers for each individual, family, and firm between 2001 and 2018. This allows us to precisely identify firm owners and to construct a panel that connects them both to fertility events and to the performance of their firms.

We begin with a rich longitudinal database that covers every resident of Norway since 1967. For each year, the database contains individual socioeconomic information (including sex, age, marital status, and educational attainment) and geographical identifiers. We also observe family identifiers that can be used to link partners to one another and parents to children. For the 2001-2018 period, we merge these data with a shareholder registry which contains security-level information on ownership of listed and unlisted shares of companies present in the Norwegian Central Securities Depository (VPS). After linking owners to firms, we merge based on balance sheet and tax record data (available from 1995-2018). Between 1995 and 2018, we also observe payroll and employment of each firm in our sample.

Using these merged registries, we first restrict our sample to individuals who owned at least 1/3 of shares issued by at least one private, non-financial limited liability company within the 2001-2018 time period. Following Levine and Rubinstein (2017), we define entrepreneurs as owners of incorporated firms.[5] Ownership can be direct or *via* pass-through entities. We further limit our sample to a "treated" group of new-parent entrepreneurs who

[4] Individuals who previously received a salary are entitled to 49 weeks of paid leave at 100% their prior salary (or 59 weeks at 80% their prior salary). These benefits can be shared between both parents. Self-employed are also entitled to these benefits at a rate that depends on their taxable income from the previous three years. Using Dutch data, Ferrando et al. (2025) show that the availability of maternity leave benefits may reduce the gender gap in entrepreneurship.

[5] Sole proprietors are harder to identify in the data and information on their firm's outcomes is limited to the business income of the owner.

had their first child between 2002 and 2018 (and owned a firm that was at least one-year-old in the year prior to childbirth) and a comparison group of entrepreneurs which did not become parents during the same time period. In total, our sample includes 211,382 unique entrepreneurs who own 267,565 firms.

Our main outcome of interest is profits before owner salary, i.e., the difference between total revenues and total costs net of any wage payments to the owner(s). This is a more direct measure of the economic performance of the firm because it is what is left for the owner to distribute after all inputs and operating expenses have been paid for. It will be allocated to dividends, kept in the firm as retained earnings (i.e., reflecting a capital gain), or assigned by the entrepreneur as compensation for the labor he/she has put into the firm—in other words, it is a global measure of the return to the (human and financial) capital the owner allocates to the business. Since there are tax and other strategic considerations from paying oneself dividends vs. paying a wage, we prefer this measure to the traditional operating profit measure (i.e., the difference between total revenues and operating costs). From now on, we refer to our preferred outcome measure simply as "profits", and we similarly define "costs" as operating costs net of wage payments to owners. For robustness, we also present results in Appendix Table A1 using the traditional operating profits measure and find qualitatively similar results in the post-childbirth period. Moreover, we investigate the evolution of revenues and costs separately. Finally, we study how childbirth affects whether a firm is active (defined as reporting positive revenues) and the log of firm employment (defined as the number of employees, including the owners).

Table 1 summarizes our data, separately by gender and parental status. Columns (1) and (4) pool statistics across our sample period for all non-parent entrepreneurs, while columns (3) and (6) do the same for new parent entrepreneurs. As expected, new parent entrepreneurs tend to be younger. They are also more likely to have college education than non-parent entrepreneurs and to be married/cohabiting.[6] Mostly because of the age difference, their companies tend to be of more recent formation. New parents are less likely to own firms in manufacturing and retail, among others, and more likely to own firms in accommodation and food service and in tech. Some differences are stark: for example, female entrepreneurs with children are twice as likely as other female owners to own firms in the "other service"

[6]Some of these differences may be mechanical, as couples are only identified as cohabiting in our data if they share a child.

industry, which primarily includes beauty salons, dry cleaners, and goods repair shops.

To allow for more meaningful comparisons, columns (2) and (5) re-weight non-parent firm owners to match the distribution of firm age, firm industry, and calendar year in the sample of parent entrepreneurs, separately by gender (using the procedure detailed in the next section). After re-weighting, non-parents mechanically match the new parents on the observable firm characteristics of age and industry, as shown in Panel B.[7] Comparison of columns (2) and (5) shows that there are important differences between male- and female-owned firms. Regardless of parental status, female-owned firms are more likely to be in industries like retail or services than in construction or manufacturing.

In Panel C we report average profits, revenues, costs, and total salaries paid to firm owners (with medians in square brackets). The re-weighted statistics for non-new parents are generally closer to those of new parents relative to unweighted statistics. However, some differences remain: revenues, costs, and profits tend to be marginally higher at new mothers' firms, suggesting that these firms operate at a slightly larger scale. We also note that the number of female entrepreneurs in our data is less than a third of the number of male entrepreneurs, which mirrors aggregate statistics. Among non-parents, businesses owned by female entrepreneurs are smaller, with 36 percent lower revenue, 28 percent lower profits, and 12 percent fewer employees than businesses owned by male entrepreneurs.

3 Empirical Strategy

Our population of interest is entrepreneurs who owned a business in the year preceding childbirth, and our objective is to document how business performance evolves after the birth of the child. To do so, we implement a matching strategy that compares firms owned by new parents with firms with similar characteristics owned by other entrepreneurs.

We first group the "treated" entrepreneurs into cohorts based on the year g in which their first child was born. We require each entrepreneur i to own at least 1/3 of at least one firm j in year $g-1$. We limit our analysis to firms that had been started in years $g-2$ and earlier, i.e., *before* pregnancy. We then construct a cohort-specific control group for each cohort g by identifying a set of entrepreneurs who satisfy the same requirements—that is,

[7] Re-weighting on age is based on indicators for firm age up to 20 and a single indicator for being over 20 years old. For this reason, the averages of firm age in Table 1 differ very slightly between parents and re-weighted non-parents.

they owned at least $1/3$ of at least one firm j in year $g-1$, which had been started in year $g-2$ or earlier—but who did not become parents between years $g-5$ and $g+10$, which are the periods for which we will estimate dynamic differences in performance. We can define treatment and control samples for each of the years (cohorts) 2002-2018. We follow firm outcomes throughout the post-event period even if ownership changes in or after the year of birth.

Entrepreneurs who have children during our sample period tend to own younger firms, as seen in Table 1. An unadjusted comparison between treated and control firms might therefore pick up substantial differences in growth patterns unrelated to childbirth. Moreover, growth patterns could be industry-specific. We thus construct estimation weights that allow us to adjust non-parametrically for industry-specific growth patterns. For each cohort g, we construct estimation weights so that the joint distribution of firm age, firm industry, and owner's gender are the same in the treatment and control samples in each calendar year. To maximize overlap in these variables between treatment and control, we use the broad industries shown in Table 1. Our results are qualitatively similar if we match on more granular levels (see Appendix Table A1). Further details on weighting are provided in Appendix B. This method applies the matching approach of Heckman, Ichimura and Todd (1997, 1998) as extended by Callaway and Sant'Anna (2021) to a dynamic setting.

We implement this approach by stacking treatment and control samples across cohorts and then estimating a weighted regression, separately for men and women.[8] Let Y_{ijks} denote the outcome for entrepreneur i's firm j in calendar year s, with k indexing the cohort-specific samples. Let the binary variable D_{ik} indicate being in the treated sample. We estimate via least squares the stacked regression:

$$Y_{ijks} = \sum_{g} \mathbb{1}[k=g] \left(\alpha^g + \gamma^g D_{ik} + \sum_{t \neq -2} (\lambda_t^g + \beta_t^g D_{ik}) \mathbb{1}[s=t] \right) + f(X_{ijs}) + \varepsilon_{ijs} \qquad (1)$$

where $t = s - g$ indexes time relative to childbirth and $f(X_{ijs})$ are additional covariates specified additively. We include our matching variables (firm age and industry) as covariates, along with full sets of dummies for owner age and education level. To account for firm entry

[8]Estimating a stacked regression allows us to properly cluster on the firm- and entrepreneur-levels, accounting for the fact that some individuals appear in multiple cohorts (and thus have duplicated outcomes). It also allows us to control for extra covariates in additive fashion. See Baker, Larcker and Wang (2022) for further discussion on the merits of stacked regression in event study settings.

in the pre-period, we also include full sets of indicator variables for firms existing in each period $t \in \{-5, -4, -3\}$ interacted with treatment and cohort indicators. This last set of indicators improves the estimation of the $t \leq -3$ pre-treatment periods and does not affect the other estimates.

The regression produces a set of cohort-specific event study estimates, $\hat{\beta}_t^g$. To obtain an overall estimate of the child penalty, $\hat{\beta}_t$, we simply weight these cohort-specific estimates by the size of each cohort's treated group:

$$\hat{\beta}_t = \sum_g \omega_g \hat{\beta}_t^g \quad \text{where} \quad \omega_g = \frac{\sum_i D_{ik} \mathbb{1}[k = g]}{\sum_i D_{ik}}. \tag{2}$$

These aggregated event study estimates show how performance trends for new parents differ from those of other entrepreneurs around the time of childbirth. By following entrepreneurs from five years before childbirth until ten years after childbirth, we capture not only the initial responses in performance after the child arrives but also any medium-term adjustments while maintaining a stable sample of firms. Alongside our dynamic (event study) results, we also report a simple average for the 10-year post-childbirth period:

$$\hat{\beta}_{\text{post}} = \frac{1}{10} \sum_{t=1}^{10} \hat{\beta}_t. \tag{3}$$

This estimate provides a summary measure of the post-treatment change in firm performance. In all cases, inference is based on a cluster-robust variance matrix with multi-way clustering on the entrepreneur- and firm-levels.

The final issue to discuss is the quantitative interpretation of the coefficient estimates. Since women tend to run smaller firms than men, it would be more appropriate to use percentage change in profits as our main outcome of interest. Unfortunately, profits are frequently zero or negative, precluding the use of log or similar transformations (see Chen and Roth 2023). Hence, we follow Kleven, Landais and Søgaard (2019) and transform our estimates into percent changes in profits relative to what our regression model predicts profits would have been if the entrepreneurs had not had a child (which we call $\hat{\psi}_t$). Formally, $\hat{\psi}_t = \hat{\beta}_t / \hat{\pi}_t$, where $\hat{\beta}_t$ comes from (2), and $\hat{\pi}_t$ averages across the cohort-specific predicted values $\tilde{Y}_{ijks}$ which are based on the estimates from (1) but with D_{ik} set equal to zero in the prediction.[9] This percentage change in profits is what we plot in our key exhibit, Figure 1.

4 Results

4.1 Main findings

We begin by examining our primary outcome of interest, which is how firm profits change around the time of the birth of the first child of the entrepreneur (Figure 1). Following the empirical strategy described in section 3, we find that firms owned by first-time mothers experience an average 23% decline in profits relative to comparable firms owned by female-led firms where the owner experiences no childbirth during the sample period. The decline in profits is visible in the year of childbirth (around –7%), it accelerates in the following years, and hovers around -30% after a decade since childbirth. The effect for first-time fathers is much smaller (around -4%) and statistically insignificant. Moreover, the year-by-year analysis reveals no clear economically relevant pattern. For both men- and women-owned firms we observe no significant anticipatory effects or pre-trends in the years leading up to the birth.

Table 2 digs deeper into the main result and adds further context to it. In all specifications we divide the sample periods into four sub-periods: the pre-parenting year ($t = -2$, which is also the omitted category), the year of pregnancy ($t = -1$), the year when the child is born ($t = 0$), and the post-childbirth years ($t > 0$). Column (1) reproduces the results for profits of Figure 1, but in levels rather than percentage terms. Profits at female-led firms are, in the post-childbirth years, US$22,000 lower on average relative to the baseline. There is a smaller and statistically insignificant child penalty for fathers.

In column (2) we look at the child penalty effect on owner salaries. For women, the effect parallels that for profits. There is a strong decline in wage salaries in the year of childbirth as well as in the post-childbirth years, as well as evidence of intertemporal substitution while pregnant.[10] The wage decline following childbirth is partly insured by the generous parental leave benefit policy which is available also for self-employed workers in Norway. The positive

[9] That is, $\tilde{Y}_{ijks}$ is the regression-predicted mean outcome in the absence of treatment at event time t.

[10] The reduction in personal earnings among female entrepreneurs upon motherhood is similar to that observed among non-entrepreneurs, as we show in Appendix Figure A1. For both groups, we find substantial declines in earnings (net of maternity benefits), consistent with Andresen and Nix (2022).

increase in wages in the year preceding childbirth is also visible among male entrepreneurs, it persists in the year of childbirth and disappears afterwards.

Changes in firm profits generally do not fully reflect any underlying changes in firm scale. For example, when the profit margin (the profits-to-revenues ratio) is small, minor relative changes in revenues and/or costs can lead to substantial relative changes in profits. To better understand the relationship between childbirth and firm scale, we look at effects on both components underlying firm profits: revenues and costs. Because revenues and costs are each strongly right-skewed, we log-transform these variables prior to estimation.[11]

The results are reported in columns (3) and (4). These columns reveal an important difference between female- and male-led firms that is not visible from the average profits results. While mothers shrink the size of their businesses (both costs and revenues decline), fathers' firms appear to expand it (costs and revenues increase concurrently). For men, there is evidence that their costs and revenues responses begin in the year in which information about future childbirth is revealed, perhaps reflecting the desire to leave a larger (or more successful) business to their heir. We further explore the size issue in column (5), where we look at the effect of childbirth on number of workers employed by the firm. Consistent with the results above, father-led firms expand employment, while the estimates for mothers are statistically insignificant.

In columns (6) and (7), we look at extensive margin effects: whether the firm is active (reporting positive revenues) and the hazard rate of selling the firm. There is no significant effect on the extensive margin of firm activity. In contrast, both mothers and fathers have a higher likelihood of selling their firms than entrepreneurs in the control group. This increase is 1.2 percentage points for women in the year when the child is born and 0.7 percentage points over the post-childbirth period, and it is 0.4 percentage points for men. While the child penalty on this particular dimension appears large relative to the average, note that the average itself is rather small: in our whole sample, only 1.8% of female -owned firms and 1.4% of male-owned firms are sold in each post-event period.

[11] Note that percentage changes in profits are equal to a weighted average of percentage changes in revenues and percentage changes in costs. While the weights themselves sum to one, the weight on revenues exceeds one (since it is equal to the inverse of the average profit margin). This means that even if costs decline proportionally more than revenues, there is still a decline in profits – as we find empirically.

4.2 Heterogeneity analysis

What explains the child penalty for female entrepreneurs? One obvious explanation is the demands of child bearing and child rearing, which may exert a much larger effect on female entrepreneurs than male entrepreneurs. This may take many forms, from declining participation in the activities of the firm due to parental leave to the physical and emotional toll associated with pregnancy, childbirth, and child rearing (including, e.g., breastfeeding). In perfectly competitive labor markets it would be possible, at least in principle, to substitute the missing or declining effort of the entrepreneur with a replacement worker. On the other hand, the creativity and effort that an entrepreneur brings to her business may be irreplaceable, especially those of a firm founder. Assuming that the decline in time spent at the firm due to childbirth is independent of entrepreneurial ability, it stands to reason that the child penalty should be larger for entrepreneurs whose role in the firm is more vital to the firm's fortunes.

To obtain a measure of entrepreneurial ability and test this hypothesis, we estimate a firm performance fixed effect regression using pre-pregnancy data for parents and all available data for non-parents. We interpret the fixed effect estimate as a measure of the entrepreneur's ability. We first residualize log revenues on owner age dummies and interactions of firm industry dummies with each of the following: firm size (log assets and log employment), firm age dummies, and calendar year dummies. We take as an entrepreneur's fixed effect the average residual of these regressions up to the year before birth. We then use these estimated fixed effects to rank entrepreneurs into four ability groups, corresponding to deciles 2-3, 4-5, 6-7, and 8-9 of the distribution of estimated fixed effects.[12] We exclude the bottom and top decile since estimated fixed effects are noisier in the tails of the distribution. The estimated child penalty for female and male entrepreneurs in the different ability groups is shown in Figure 2. There is a clear increase in the magnitude of the child penalty for more talented entrepreneurs, with the top group experiencing an over 35% decline in profits while the bottom group displays a statistically insignificant effect. For men, the effect is negative and significant at the 5% level only for the most talented ones.[13]

An important dimension of heterogeneity in the child penalty is the presence of mech-

[12] For comparability, these deciles are determined by the distribution of fixed effects for mothers. However, the distributions for mothers and fathers are quite similar.

[13] An alternative explanation is that more talented entrepreneurs take more time off following childbirth. Unfortunately, we do not have data to check whether this is the case.

anisms that allow entrepreneurs to attenuate it. Parental leave benefits are universal in Norway. However, the existence of business or marriage partners may be relevant forms of insurance against the child penalty shocks. We show evidence of this in Table 3, where we focus on female owners since this is the group most affected by the child penalty. In the first two columns we compare the child penalty for firms where the new mother is the primary stakeholder in the business (greater than 50% ownership) to those who have co-owners. When the new mother is the primary stakeholder, the firm experiences a significant 10% decline in profits in the year of the child's birth. When the mother is one of multiple co-owners, this effect is only -3% and is statistically insignificant. One possible explanation is that the presence of co-owners smoothens the shock by leaving a co-owner in charge of the firm when the other co-owner is out, at least temporarily. Nevertheless, we note that a longer-run penalty exists for co-owned firms as well, albeit slightly smaller.

A different insurance mechanism appears to be at play when we compare entrepreneurs who have a spouse (or cohabitor) who is employed vs. those that do not. If non-employed spouses can more easily share some of the burden of child rearing, we might expect the child penalty of female entrepreneurs with non-employed spouses to be attenuated. This is indeed the case: at the time of birth, profits decline by 10% for entrepreneurs with employed spouses while the estimate is positive and insignificant for entrepreneurs with non-employed spouses. The average post-period penalty for entrepreneurs with non-employed spouses remains less than half of that for those with an employed spouse (-9% as opposed to -21%), and it is insignificant.

Finally, we explore whether the decline in profits may be due to statistical discrimination by customers, who may avoid working with a firm run by a pregnant entrepreneur if they expect lower reliability and commitment to the business in the future. The loss of customers during pregnancy may cause a persistent loss in business opportunities, ultimately resulting in a drop in revenue and profits. To test this hypothesis, we first match the firms' subindustry descriptions to the most closely related occupation in O*NET, a database maintained by the U.S. Department of Labor. We describe the matching procedure in detail in Appendix C. For example, the industry "Hairdressing and other beauty treatment" is matched with the occupation "Hairdressers, Hairstylists, and Cosmetologists." Within the O*NET database, we can observe what share of individuals in each occupation engage in face-to-face discussions on a daily basis. If this share exceeds 80%, which is approximately the mean in our sample of entrepreneurs, we classify the industry as having higher face-to-face contact. As shown in the last three columns of Table 3, we do not find systematic differences in how motherhood affects the profits of firms in sectors that require greater face-to-face contact compared to other sectors. This finding does not rule out the possibility that statistical discrimination may operate through different channels.

4.3 Additional Evidence from Survey Data

Gender norms lead mothers, including those who are entrepreneurs, to bear disproportionate child-related responsibilities relative to fathers. Our administrative data do not include information on hours worked or hours devoted to childcare. However, we secured access to survey data that Statistics Norway collected over the period 2008-2023 in coordination with the EU-mandated Survey on Income and Living Conditions (EU-SILC).

Besides key demographics (age, gender, age of the youngest child), the survey includes information on hours of work (for those currently employed), occupation, and—for those who report being self-employed—the number of employees they employ. Since our main analysis excludes sole proprietors, to approximate the entrepreneurs in our administrative data we focus on self-employed individuals who have at least one employee working for them. Appendix Table A2 reports summary statistics about this sample, which includes 244 women and 647 men. Among these, 49% of women and 56% of men have at least one child. Average weekly hours of work are equal to 41 for women and 49 for men.

Using the EU-SILC cross-sectional data, we estimate the child penalty on entrepreneurs' average weekly hours of work. Specifically, we compare parents with children aged 0-10, mirroring the sample used in the administrative data, to entrepreneurs without children, controlling for a quadratic in age, marital status, education, and industry.

The results, reported in Figure 3, show that mothers work significantly fewer hours than non-mothers (between 10 and 15 fewer hours) in the first 5 years of the child's life, while the difference between father and non-father entrepreneurs is much smaller and statistically insignificant. The effect is persistent, although it becomes noisier for mothers of school-age children.[14]

[14] EU-SILC participants also report their health status. We assume that individuals have above average health if they report "excellent" or "very good" health status. Using the same strategy adopted to study the impact of childbirth on hours, we find that mother entrepreneurs are less likely to report being in good health than non-mothers (a 20 percentage point difference), as shown in Appendix Figure A2. The effect is

This finding suggests that a change in entrepreneur's investment of time in the business may contribute to the reduction in firm profits associated with motherhood that we have documented using the Norwegian administrative data.

5 Concluding Remarks

There is an active debate in the literature regarding the causes of the gender gap in female entrepreneurship. In this paper, we document the existence of a substantial "child penalty" for female entrepreneurs and their firms. Childbirth is associated with a 20-30% decline in business profits in the years that follow the birth of a child, while for men the penalty is economically small and statistically insignificant. We find that businesses owned by women shrink in size (a decline in both revenues and costs); moreover, they are more likely to be sold following childbirth.

What explains the child penalty among female entrepreneurs? One possibility is that a decline in profitability is the cause rather than the effect of childbirth. For example, female entrepreneurs whose business is on a declining path could respond by having a child, or changing its timing. However, we find no evidence that—in the pre-childbirth period—performance of future mothers-led firms is statistically different than the performance of control firms that share the industry and the year of foundation of the treated firms, and whose owner is a woman who did not become a parent during our sample period.

A more likely explanation is the change in effort put in the business as a consequence of childbirth. In perfectly competitive labor markets, it would be possible to replace the time of the entrepreneur with that of a surrogate managers or other executive. Yet entrepreneurs, and even more so founders, are a source of hard-to-replace creativity, strategic thinking, experience, and leadership, that goes beyond the hours they put in their business. We use Norwegian survey data to show that mothers work fewer hours in their business compared to non-mothers, especially in the first few years of the child's life. Over and above a change in work hours, child-bearing and child-rearing have also well-documented physical and emotional costs that may impact productivity. We have provided three additional pieces of evidence consistent with this explanation. First, the child penalty is attenuated for female

significant at the 10% level only for mothers of young children (aged 0-3) and noisier for mothers of older children. There is no statistically significant difference between father and non-father entrepreneurs.

entrepreneurs who can delegate more of their child rearing to a marriage partner (i.e., if their partner is unemployed). Second, the penalty is also attenuated if the entrepreneur can delegate the conduction of the business' affairs to a business partner (i.e., if the woman owns no more than 50% of the firm). Finally, we find that the child penalty is larger for more talented entrepreneurs, since their absence is more "costly".[15]

A different explanation comes from demand rather than supply considerations. Suppose that customer, client, or supplier relationships were highly personal, as might be the case for doctor-patient, lawyer-client, or financial adviser-investor relationships (especially those that occur on a continuous, long-term basis). This relationship may generate a form of customer-based form of statistical discrimination. The client may interpret the pregnancy of the business owner as a signal of the latter's low future work commitment, and respond by switching to a different provider. A *prima facie* indication that this may well be a potential mechanism is the absence of a child penalty for fathers, whose future fatherhood may be more easily concealed. While it is difficult to find exogenous variation in signals of future work commitment, a simple regression where we look at industries in which entrepreneurs are more likely to have direct contact with clients (e.g., services) and those where this is less likely (e.g., manufacturing) reveals no statistically significant difference in the child penalty in profits in this dimension.

Overall, our findings suggests that entrepreneurial effort is a key input in firm profits that is differentially influenced by motherhood and fatherhood. A change in the time demands of an entrepreneur after childbirth has lasting effects on firm performance when the entrepreneur is female. Childcare responsibilities, perhaps related to traditional gender norms (Kleven, Landais and Leite-Mariante, 2024), are likely to be the primary contributor to the decline in profits that follows childbirth by a female business owner but not by a male entrepreneur, potentially contributing to the gender gap in entrepreneurship.

[15]This requires a mild condition on technology, i.e., that the hours spent at the business and the talent of the entrepreneur are gross complements in production, which would be the case if more talented entrepreneurs devoted a larger share of their time to their business.

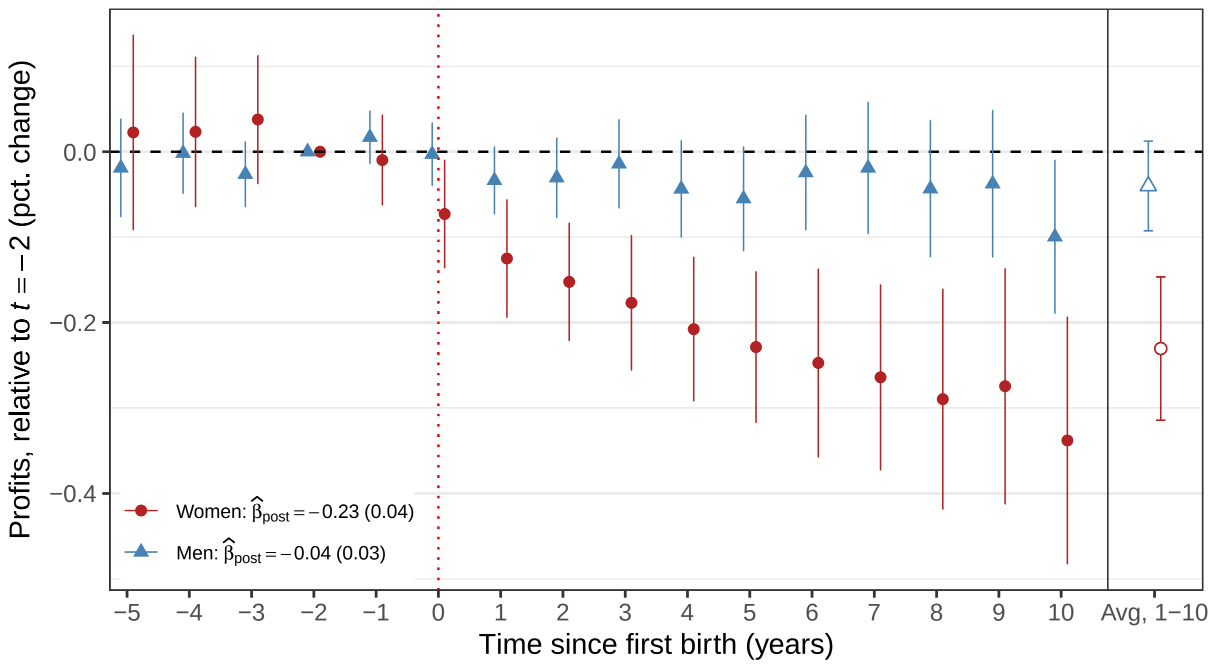
Tables and Figures

Table 1: Summary statistics in the year preceding birth

	(1)	(2)	(3)	(4)	(5)	(6)
		Women			Men	
	Control, pooled	Control, weighted	New parents	Control, pooled	Control, weighted	New parents
Panel A: Owner demographics						
Age	51.7	48.6	31.2	53.1	49.9	33.6
College education	0.335	0.351	0.448	0.318	0.318	0.357
Studied business	0.218	0.204	0.191	0.179	0.167	0.202
Married/cohabiting (at time of birth)	0.650	0.666	0.861	0.730	0.719	0.879
Panel B: Firm characteristics						
Firm age	12.5	7.1	7.1	12.6	6.3	6.4
Accommodation and food service	0.058	0.073	0.073	0.031	0.036	0.036
Administrative and support service	0.013	0.016	0.016	0.016	0.025	0.025
Arts, entertainment, and recreation	0.011	0.021	0.021	0.009	0.018	0.018
Construction	0.036	0.029	0.029	0.143	0.162	0.162
Education	0.010	0.018	0.018	0.006	0.011	0.011
Human health	0.058	0.075	0.075	0.026	0.026	0.026
Information and communication	0.019	0.032	0.032	0.042	0.078	0.078
Manufacturing	0.038	0.036	0.036	0.071	0.043	0.043
Other service	0.054	0.107	0.107	0.008	0.012	0.012
Professional, scientific, and technical	0.147	0.147	0.147	0.158	0.126	0.126
Real estate	0.197	0.156	0.156	0.189	0.196	0.196
Transportation and storage	0.018	0.017	0.017	0.045	0.037	0.037
Wholesale and retail trade	0.336	0.259	0.259	0.230	0.197	0.197
Num. employees (excl. owners)	3.8	3.1	3.5	4.3	3.0	3.0
Panel C: Balance sheets (thousands of USD)						
Profits, mean [median]	86.0	76.7	83.7	119.5	98.1	94.7
	[38.1]	[38.9]	[41.5]	[47.2]	[37.6]	[35.0]
Revenues	718.1	570.1	689.8	1,124.4	822.1	855.6
	[235.2]	[230.9]	[234.3]	[268.3]	[224.0]	[220.6]
Costs	632.0	493.3	606.1	1,004.9	723.9	761.0
	[163.4]	[160.4]	[169.4]	[181.4]	[147.8]	[148.6]
Owner salaries	30.4	41.1	41.9	34.5	40.6	41.1
	[0.0]	[12.3]	[18.8]	[0.0]	[0.0]	[0.0]
Number of owners	45,513	45,513	2,443	155,606	155,606	7,820
Number of firms	38,038	38,184	2,973	215,579	215,455	10,975

Notes: This table reports summary statistics for our sample of privately-owned Norwegian firms with at least one owner with $\geq 1/3$ ownership in the 2001-2018 period. Monetary outcomes are measured in constant 2015 USD. Profits and costs are net of owner salaries. Sample means are presented in all panels. In Panel C, we also present medians (in brackets). "New parents" had their first child in 2001-2018 and owned a firm in the year prior. "Control" did not become a parent during the same time period. Firms are weighted such that each owner in our sample receives equal weight. In columns (2) and (5), we reweight the sample of control firms to match the sample of new parents' firms on the industry $\times$ age $\times$ year level. Statistics in columns (1) and (4) are pooled over the sample period. Statistics in all other columns are measured in the year prior to when the child was born ($t = -1$).

Figure 1: Firm Profit Responses to the Birth of the Owner's First Child



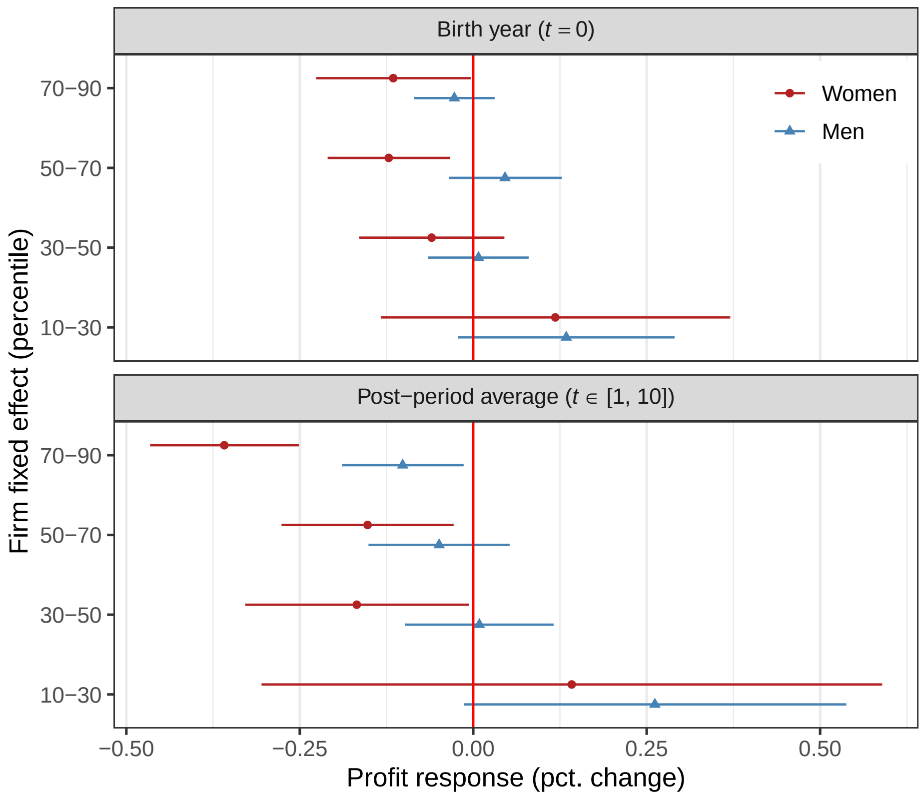
Notes: This figure plots the estimated profit responses to owner childbirth relative to $t = -2$, separately by the sex of the owner. The outcome is defined as revenues minus total operating costs (excluding owner salaries). The figure shows 95% confidence intervals based on cluster-robust standard errors, clustering on the owner and firm-levels. Event study estimates are weighted averages of cohort-specific event study coefficients, weighting by the number of new parents in each cohort. Cohort-specific control groups are reweighted to match the distribution of firm age and industry in each cohort's treated group. The regressions also include full sets of dummies for firm age, firm industry, owner age, and owner education-level. The outcome is trimmed at the 0.5th and 99.5th percentiles. The plotted event study coefficients are rescaled by an average of the predicted outcome, omitting the contribution of the treated event-time indicators in the prediction. We then take a weighted average of these predictions across cohorts, which provides the denominator for rescaling. Standard errors are obtained via the delta method to account for the estimated predictions.

Table 2: Impact of Childbirth by Gender of the Entrepreneur

	(1) Profits	(2) Owner salaries	(3) log(revenues)	(4) log(costs)	(5) Employees	(6) Firm active	(7) Sold firm
Women, $t = -1$	–820	1,303**	–0.005	–0.010	0.028	–0.001	—
	(2,279)	(608)	(0.023)	(0.023)	(0.059)	(0.005)	
Women, $t = 0$	–6,251**	–6,691***	–0.086***	–0.101***	0.104	–0.009	0.012***
	(2,869)	(804)	(0.030)	(0.030)	(0.102)	(0.007)	(0.004)
Women, $t > 0$ avg.	–22,088***	–6,978***	–0.054	–0.102*	–0.144	–0.016	0.007***
	(5,247)	(1,458)	(0.048)	(0.059)	(0.242)	(0.013)	(0.002)
$\bar{Y}$, female owners	82,581	41,453	12.411	11.721	3.217	0.881	0.018
N female owners	45,902	45,891	44,126	45,832	45,907	45,909	45,876
Men, $t = -1$	1,597	1,723***	0.038***	0.032**	-0.023	0.002	—
	(1,478)	(357)	(0.014)	(0.013)	(0.033)	(0.003)	
Men, $t = 0$	-277	2,064***	0.024	0.017	-0.046	-0.001	0.004**
	(1,817)	(456)	(0.017)	(0.017)	(0.047)	(0.004)	(0.002)
Men, $t > 0$ avg.	-4,089	114	0.044*	0.048	0.317***	-0.008	0.004***
	(2,815)	(803)	(0.027)	(0.031)	(0.110)	(0.006)	(0.001)
$\bar{Y}$, male owners	94,718	39,888	12.455	11.589	2.656	0.850	0.014
N male owners	157,635	157,610	152,510	157,455	157,667	157,671	157,586

Notes: This table reports estimates of the response of firm outcomes to firm owner childbirth, separately by the sex of the owner. Monetary outcomes are measured in constant 2015 USD. Event study estimates are weighted averages of cohort-specific event study coefficients, with weights proportional to the size of the treated sample in each cohort. Cohort-specific control groups are reweighted to match the distribution of firm age and industry in each cohort's treated group. The regression also includes full sets of dummies for firm age, firm industry, owner age, and owner education-level. $t = 0$ is the year in which the owner had their first child, and the omitted (relative) event time is $t = -2$. The $t > 0$ estimates are equal-weighted averages of the $t = 1, \ldots, 10$ estimates. Owner salaries and employees are trimmed at the 99.5th percentile, and profits are trimmed at the 0.5th and 99.5th percentiles. Salaries and profits are equal to zero if a firm is not active. In columns (1)-(6), the sample means $\bar{Y}$ are based on the treated sample at event time $t = -1$. Because we condition on ownership in $t = -1$ in our sample construction, we report the mean for the full sample in column (7). Standard errors are in parentheses and are two-way clustered on the individual and firm-levels. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.,

Figure 2: Profit Responses, by Percentiles of Firm Fixed Effect



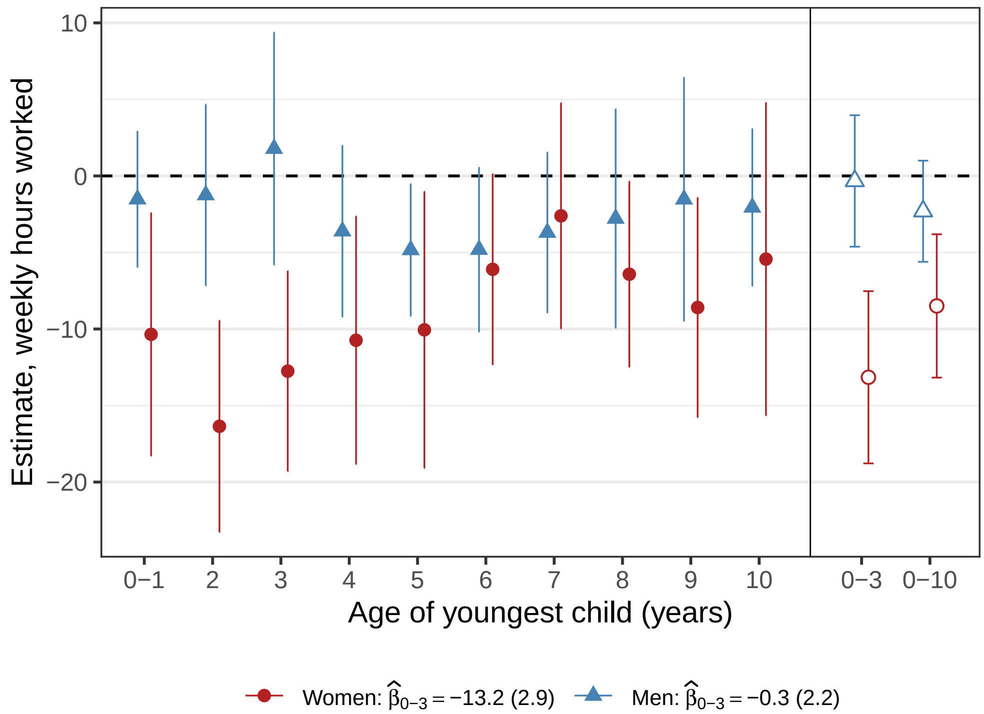
Notes: This figure plots profit response estimates separately by the sex of the owner and the binned firm fixed effect. The firm fixed effect is calculated using the control firms and the pre-treatment treated firms. Separately for male- and female-owned firms, we regress log revenues on industry dummies interacted with each of (i) log assets, (ii) log workers, (iii) firm age dummies, and (iv) calendar year dummies. We also include a set of owner age dummies. We use the average (pre-treatment) residual as the firm fixed effect. The bins are defined based on the distribution of fixed effects for the female-owned treated firms. We include the firm fixed effect bin (10-30, 30-50, 50-70, 70-90) in the weighting procedure. We estimate the specification underlying Figure 1 separately by bin, with the modification that we replace the owner age dummies with dummies for 5-year age bins in these subsamples. 95% confidence intervals are based on cluster-robust standard errors, clustering on the owner and firm-levels.

Table 3: Heterogeneous Profit Responses for Female Owners

	> 50% ownership		Spouse employed		Face-to-face contact	
Profits, pct. change	Yes	No	Yes	No	Higher	Lower
$t = -1$	0.048	–0.037	–0.004	–0.005	–0.013	0.008
	(0.038)	(0.032)	(0.029)	(0.053)	(0.031)	(0.040)
$t = 0$	–0.104**	–0.034	–0.108***	0.092	–0.044	–0.086*
	(0.044)	(0.040)	(0.032)	(0.078)	(0.038)	(0.046)
$t > 0$ avg.	–0.222***	–0.210***	–0.208***	–0.090	–0.214***	–0.196***
	(0.052)	(0.050)	(0.046)	(0.087)	(0.043)	(0.066)
Mean profits	\$67,495	\$87,965	\$85,146	\$60,620	\$79,316	\$79,276
N owners	20,710	25,803	25,597	11,304	26,774	18,598

Notes: This table reports estimates of the response of profits to firm owner childbirth for female-owned firms, separately by different firm and owner characteristics. Characteristics are measured at event time $t = -1$. Mean profits are reported for the treated sample at event time $t = -1$. In the first four columns, observations are reweighted so that the distribution of industries (SIC sections) is the same in each pair of columns. Measures of face-to-face contact for each subindustry are obtained by matching descriptions for detailed SIC industry codes to descriptions of O*NET occupations (see Appendix C for further details on this matching procedure). We classify an industry as having higher face-to-face contact if at least 80% of respondents within the matched occupation report having face-to-face discussions daily, where 80% is approximately the mean in our data. All other notes are as in Figure 1, with the modification that we replace the owner age dummies with dummies for 5-year age bins in these subsamples.

Figure 3: Entrepreneur working hours by age of youngest child



Notes: Data from the European Union Statistics on Income and Living Conditions (EU-SILC), Norway, 2008-2023. This figure plots regression estimates of weekly hours worked on the age of the entrepreneur's youngest child, along with 95% confidence intervals based on robust standard errors. Regressions are estimated separately by the sex of the entrepreneur. The control group is comprised of entrepreneurs with no children. The regressions include dummies for calendar year, firm industry, the marital status and education level of the entrepreneur, and a quadratic in entrepreneur age. The "0-3" estimate, which is also reported in the legend, is an average of the age 0-1, 2, and 3 estimates. The "0-10" estimate is an average over all ages. The sample includes self-employed individuals who have at least one employee (N = 224 women and N = 647 men).

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Supplemental Appendix

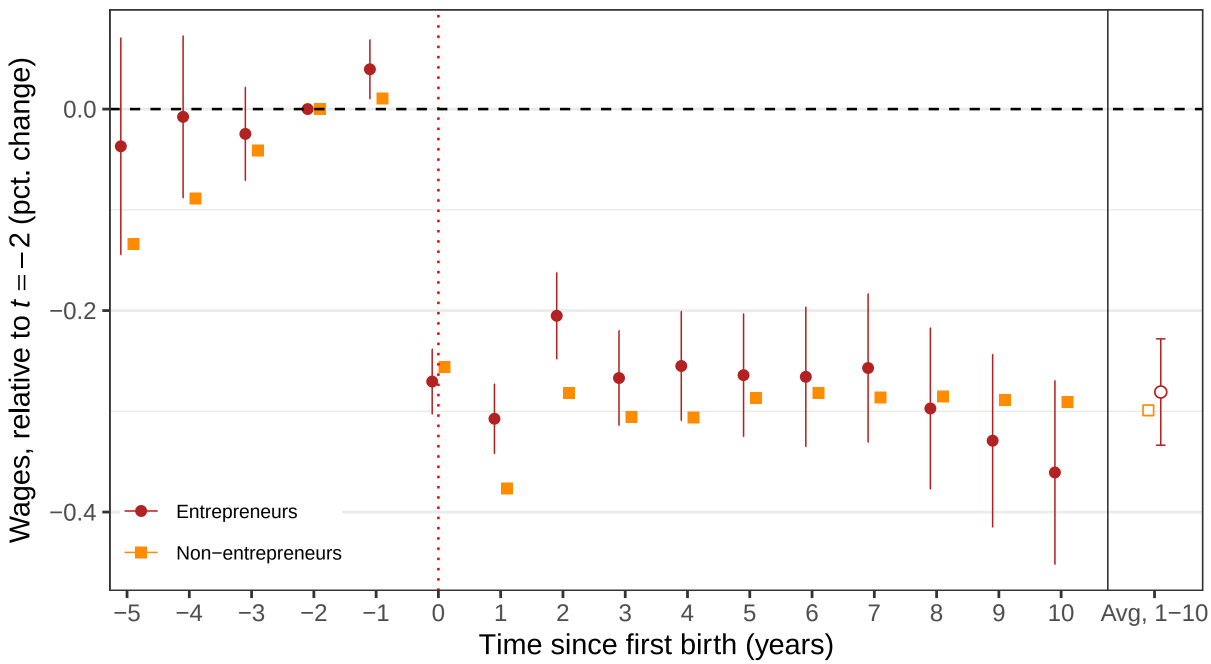
A Additional Exhibits

Table A1: Estimates for female owners under different weighting/outcomes

	(1)	(2)	(3)	(4)
	Response as percentage change			
$t = -1$	–0.010 (0.027)	–0.014 (0.025)	0.004 (0.025)	–0.022 (0.044)
$t = 0$	–0.073 (0.032)**	–0.075 (0.029)**	–0.066 (0.030)**	0.034 (0.057)
$t > 0$ avg.	–0.230 (0.043)***	–0.207 (0.038)***	–0.205 (0.038)***	–0.215 (0.063)***
	Response in levels			
$t = -1$	–820 (2,279)	–1,120 (1,981)	294 (1,963)	–943 (1,868)
$t = 0$	–6,251 (2,869)**	–6,178 (2,501)**	–5,388 (2,499)**	1,467 (2,434)
$t > 0$ avg.	–22,088 (5,247)***	–18,588 (4,198)***	–18,283 (4,194)***	–11,219 (4,090)***
Outcome variable	Profits before owner salaries	Profits before owner salaries	Profits before owner salaries	Operating profits
Weighting vars.	Firm age × SIC section	Firm age × SIC division (2-digit industry)	Firm age × SIC section × owner educ.	Firm age × SIC section
$\bar{Y}$	82,581	78,485	78,511	40,467
N owners	45,902	42,236	39,390	45,901
N firms	54,856	49,597	46,332	54,856

Notes: This table reports estimates of the response of profits to firm owner childbirth for female-owned firms under different estimation weights and outcome variables. Column (1) reproduces our estimates from Figure 1 and Table 2. Columns (1)-(3) use our preferred profit outcome, which is total revenues minus all costs except for salaries paid to firm owners. In column (4), we replace this outcome with total revenues minus total costs, where costs now include the salary paid to the owners (i.e., the outcome is operating profits). In columns (1) and (4), we follow our approach from the text and weight each control cohort to match the joint distribution of firm age and firm industry (SIC section) in the corresponding treated cohort. In columns (2) and (3), we replace the SIC section with more granular measures of industry. Column (2) weights based on SIC division, which is comprised of 2-digit industries. Column (3) weights based on the interaction between SIC section and owner education (3 levels). We drop observations with values of weighting variables for which there is no overlap between treatment and control, which reduces our sample size in columns (2) and (3). All other notes are as in Figure 1 and Table 2.

Figure A1: Earnings Penalty, Female Entrepreneurs vs. Non-entrepreneurs



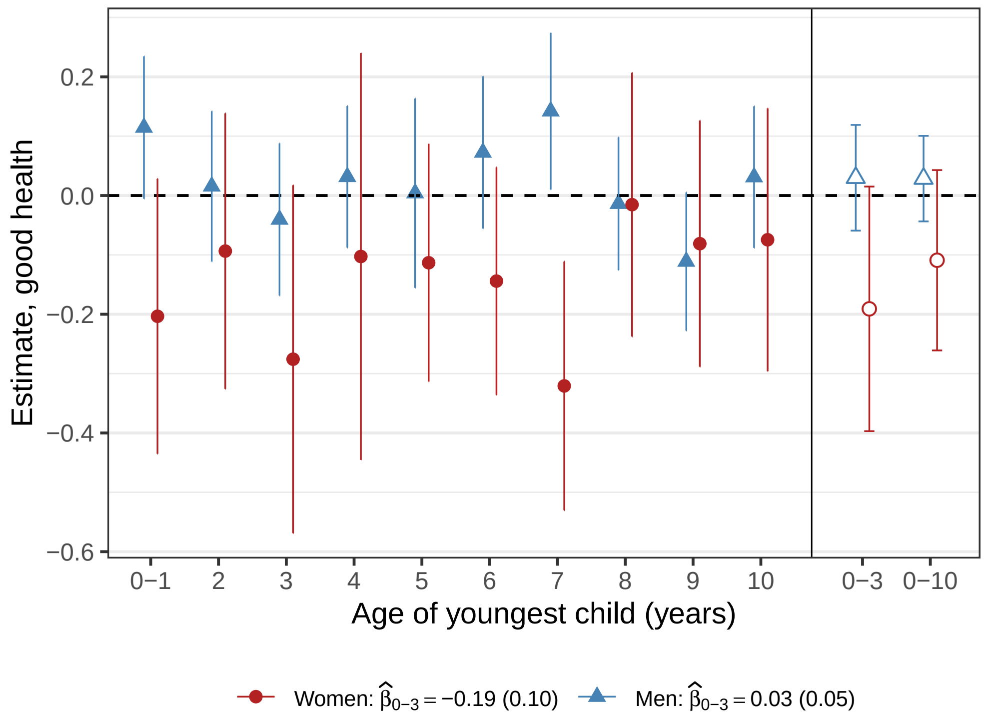
Notes: This figure compares the estimated childbirth responses of earnings relative to $t = -2$, separately for female entrepreneurs and non-entrepreneurs. The outcome for entrepreneurs is salary income paid to the entrepreneur from the entrepreneur's firm, and the sample and estimation method are the same as those underlying Figure 1. Non-entrepreneurs include $N = 413,164$ Norwegian women whose first children were born between 2001 and 2018, who were between the ages of 20 and 45 at the time of birth, and who did not own a firm during our sample period. Estimates for workers are obtained from a regression of total annual salary/wage earnings on event time dummies and full sets of dummies for individual age and calendar year. The figure shows 95% confidence intervals based on cluster-robust standard errors, clustering on the individual and (for entrepreneurs) firm-levels. The plotted event study coefficients are rescaled by an average of the predicted outcome, omitting the contribution of the treated event-time indicators in the prediction. Standard errors are obtained via the delta method to account for the estimated predictions. The 1-10 average estimates are -0.281 (s.e. 0.027) for entrepreneurs and -0.299 (s.e. 0.001) for workers.

Table A2: EU-SILC Sample: Summary Statistics by Gender

	Women		**Men**	
	Mean	SD	Mean	SD
Age	44.38	8.91	46.43	9.18
Married	0.69	0.46	0.68	0.46
College educ or higher	0.42	0.50	0.31	0.46
Has children	48.52	46.73	55.54	46.82
Number of children	1.26	1.36	1.09	1.31
Age of youngest child	9.61	7.29	8.60	7.03
Good health	0.43	0.50	0.41	0.49
Weekly hours of work	41.09	11.65	48.85	14.54
Observations	224		647	

Notes: Data from the European Union Statistics on Income and Living Conditions (EU-SILC), Norway, 2008

Figure A2: Self reported health of the entrepreneur by age of youngest child



Notes: Data from the European Union Statistics on Income and Living Conditions (EU-SILC), Norway, 2008-2023. The figure plots regression estimates of a "good health" indicator on the age of the entrepreneur's youngest child, along with 95% confidence intervals based on robust standard errors. The outcome takes a value of one if the individual reports being in excellent or very good health, and zero otherwise. Regressions are estimated separately by the sex of the entrepreneur. The control group is comprised of entrepreneurs with no children. The regressions include dummies for calendar year, firm industry, the marital status and education level of the entrepreneur, and a quadratic in entrepreneur age. The "0-3" estimate, which is also reported in the legend, is an average of the age 0-1, 2, and 3 estimates. The "0-10" estimate is an average over all ages. The sample includes self-employed individuals who have at least one employee. The sample includes self-employed individuals who have at least one employee ($N = 224$ women and $N = 647$ men).

B Estimation

This section provides a more precise description of our estimation procedure. We perform this procedure completely separately for men and women. This conditioning remains implicit throughout the remainder of this section.

Let $\mathcal{S}$ denote the entire set of observed entrepreneur-firm combinations, ij, where i indexes entrepreneurs and j indexes firms. Define $\mathcal{S}^1(g) \subset \mathcal{S}$ as the set of entrepreneur-firms ij which are "treated" in year g. For each $ij \in \mathcal{S}^1(g)$, we require each of the following to hold:

1. Entrepreneur i's first child was born in year g.
2. i owns a (weak) plurality of shares in firm j in year $g-1$, and i's ownership share must be no less than $1/3$ in this period.
3. Firm j must have been started in year $g-2$ or earlier.
4. Firm j must not appear in $i'j \in S^1(t)$ for any i' for any $t < g$.

The first requirement is the essence of treatment. The second eliminates minority stakeholders who are more plausibly investors than entrepreneurs. The third ensures that we focus on firms started prior to pregnancy. The fourth removes firms that appeared in the treated sample in an earlier cohort, which might occur if, for example, two individuals co-own a firm and have children in different years.[16]

We define $\mathcal{S}^0(g) \subset \mathcal{S}$ as the set of entrepreneur-firms which are "control" entrepreneur-firms in year g. For each $ij \in \mathcal{S}^0(g)$, we require each of the following to hold:

1. Entrepreneur i did not have their first child $t \in [g-10, 2018]$. 2018 is the final year we observe births.
2. Entrepreneur i owns a (weak) plurality of shares in firm j in year $g-1$, and i's ownership share must be no less than $1/3$ in this period.
3. Firm j must have been started in year $g-2$ or earlier.

[16] We place an additional requirement on male-owned firms, which is that the owner's female spouse must not co-own the firm or work at the firm in $t \in \{-2, -1, 0\}$. This eases the interpretation of our estimates for new fathers and does not substantively change our estimates.

4. Entrepreneur i has no co-owner i' of firm j such that $i'j \in \mathcal{S}^1(t)$ for any t. That is, firm j is not treated via a different co-owner.

The first and fourth requirements isolate a "clean" comparison to entrepreneurs who did not have any children during the comparison period. The second and third requirements are the same as the requirements for the treated sample.

We construct estimation weights so that the weighted joint distribution of firm age and sector in each control sample $\mathcal{S}^0(g)$ matches the distribution in the corresponding treated sample $\mathcal{S}^1(g)$. For an entrepreneur-firm $ij \in \mathcal{S}^0(g) \cup \mathcal{S}^1(g)$, these weights are

$$\omega_{ij}^g = \begin{cases} \theta_{ij}^g & \text{if } i \in \mathcal{S}^0(g) \\ \theta_{ij}^g \left(\sum_{k\ell \in \mathcal{S}^1(g)} \theta_{k\ell}^g \mathbb{1}\{X_{k\ell} = X_{ij}\}\right) \left(\sum_{k\ell \in \mathcal{S}^0(g)} \theta_{k\ell}^g \mathbb{1}\{X_{k\ell} = X_{ij}\}\right)^{-1} & \text{if } i \in \mathcal{S}^1(g) \end{cases}$$

$$\text{with} \quad \theta_{ij}^g = \left(\sum_j \mathbb{1}\{i \text{ owns } j \text{ in } g-1\}\right)^{-1}. \tag{4}$$

The covariates X include firm age (top-coded at 20) and firm sector (SIC section).[17] When we estimate heterogeneity as in Figure 2 and Table 3, we also include the stratifying variable in our matching variables X. The baseline weight θ_{ij}^g is the inverse of the number of firms owned by entrepreneur i in year $g-1$. This ensures that all treated entrepreneurs receive equal weight in our analysis, as opposed to placing greater weight on individuals who own multiple firms.

This weighting procedure applies the intuition of Heckman, Ichimura and Todd (1997, 1998) as extended by Callaway and Sant'Anna (2021). The insight of Heckman, Ichimura and Todd (1997, 1998) is that if treatment is randomly assigned conditional on covariates X, then matching on these covariates will provide a consistent estimate of the average treatment effect on the treated (ATT). Callaway and Sant'Anna (2021) extend this approach (which they call an "outcome regression" approach) to a dynamic setting with multiple cohorts.

We construct a stacked sample as

$$\mathcal{S}^{\text{stack}} = \{\mathcal{S}^0(2002), \mathcal{S}^1(2002), \ldots, \mathcal{S}^0(2018), \mathcal{S}^1(2018)\}. \tag{5}$$

Some observations will naturally appear in the stacked sample multiple times, which occurs

[17] Our sample construction also implicitly conditions on calendar year.

frequently in the control sample. To account for this when conducting inference, we cluster our standard errors two-way on the entrepreneur i and firm j levels.

Using the stacked sample $\mathcal{S}^{\text{stack}}$, we estimate (1) using the implementation developed by Correia (2016). We aggregate across estimates using (2), treating the shares ω_g as fixed when computing the standard errors. This approach follows closely the "stacked regression" recommended by Baker, Larcker and Wang (2022), with the primary difference being that they discuss weighting by the inverse of the estimated variance while we weight by cohort size.

In Figure 1, we transform $\hat{\beta}_t$ into a measure of percent change by following Kleven, Landais and Søgaard (2019). Specifically, we predict the outcome using the regression coefficients from (1) but with D_{ik} fixed at 0:

$$\tilde{Y}_{ijks} = \sum_g \mathbb{1}[k = g] \left(\hat{\alpha}^g + \sum_{t \neq -2} \hat{\lambda}_t^g \mathbb{1}[s = t] \right) + \hat{f}(X_{ijs}). \tag{6}$$

We then take

$$\hat{\pi}_t = \sum_g \omega_g \hat{\pi}_t^g \tag{7}$$

where $\hat{\pi}_t^g$ is the average prediction $\tilde{Y}_{ijks}$ for the treated individuals in cohort g, $ij \in \mathcal{S}^1(g)$. We report in Figure 1 the estimates $\hat{\psi}_t = \hat{\beta}_t / \hat{\pi}_t$. Standard errors are computed by the delta method, noting that $\hat{\pi}_t^g$ can be written as a weighted average of regression coefficients with weights based on the sample characteristics.

Prior to estimation, we make two adjustments to our outcome variable when the outcome is profits or owner salaries. First, we trim the outcome variable at the 99.5th percentile (profits and salaries) and the 0.5th percentile (profits). This is to mitigate the influence of extreme values, and our estimates are not sensitive to these trimming thresholds. Second, if a firm pauses or ceases activity and therefore does not report a balance sheet, we infer that profits and salaries are equal to zero. This allows us to maintain a balanced set of firms in the post-period.

C Matching occupations to industries

We begin with a set of industries based on the Norwegian Standard Industrial Classification (SIC) system[18] and a set of occupations from the Occupational Information Network (O*NET) 28.0 database.[19] For each SIC industry, we observe a brief industry description. For each O*NET occupation, we observe a title and a more detailed occupational description.

We concatenate occupational titles and descriptions and then match them to industry descriptions based on a semantic similarity measure derived from a pre-trained language model. Specifically, we use a pre-trained SentenceTransformer model (all-MiniLM-L6-v2) to encode both industry descriptions and the combined occupation texts into high-dimensional embeddings that capture semantic meaning. Using these embeddings, we compute cosine similarity scores between each industry's description and all occupation vectors. For each industry, the occupation with the highest cosine similarity is identified as the best match. This process systematically associates each industry with the occupation that most closely aligns with its description in terms of semantic content.

Table A3 shows the matched industry-occupations for the most common industries of female owners who have children. The matched occupations appear to provide a representative occupation for their respective industries. Even if it is likely that the entrepreneur is in a different occupation than the matched occupation, this is only problematic if the matched occupation and the true occupation differ in terms of face-to-face contact. For example, although the owner of a restaurant may not wait tables, it is sufficient that the restaurateur engages with clientele at a similar level. In small firms, as those in our data, this seems likely.

[18] https://www.ssb.no/en/klass/klassifikasjoner/6

[19] https://www.onetcenter.org/database.html

Table A3: Industries matched to O*NET occupations

SIC code	Industry description	Matched O*NET occupation
96.020	Hairdressing and other beauty treatment	39-5012.00: Hairdressers, Hairstylists, and Cosmetologists
68.209	Other letting of real estate	11-9141.00: Property, Real Estate, and Community Association Managers
56.101	Operation of restaurants and cafes	35-3031.00: Waiters and Waitresses
86.909	Other human health activities	21-1094.00: Community Health Workers
70.220	Business and other management consultancy activities	13-1111.00: Management Analysts
47.710	Retail sale of clothing in specialised stores	13-1022.00: Wholesale and Retail Buyers, Except Farm Products
85.510	Sports and recreation education	25-1193.00: Recreation and Fitness Studies Teachers, Postsecondary
75.000	Veterinary activities	31-9096.00: Veterinary Assistants and Laboratory Animal Caretakers
86.230	Dental practice activities	31-9091.00: Dental Assistants
68.100	Buying and selling of own real estate	41-9022.00: Real Estate Sales Agents
74.101	Industrial design, product design and other technical design	27-1021.00: Commercial and Industrial Designers

Notes: Industries and occupations are matched as described in the text. This table presents the 10 most common 5-digit SIC industries based on SIC 2007.