UNIVERSITY OF GOTHENBURG

SCHOOL OF BUSINESS, ECONOMICS AND LAW

From She-Cession to She-Covery?

Alva Ohlsson & Elin Skoogsberg

Supervisor: Sanna Bergvall

Master's thesis in Economics, 30 hec

Spring 2024

Graduate School, School of Business, Economics and Law, University of Gothenburg, Sweden

From She-Cession to She-Covery?

Alva Ohlsson & Elin Skoogsberg

20th June 2024

Abstract

In response to the COVID-19 pandemic, restrictions imposed had a disproportionate effect on women, leading to an economic downturn referred to as the "she-cession". This thesis investigates the transition from she-cession to she-covery, with a focus on how the ease of pandemic restrictions has influenced women's participation in the labor force. By analyzing comprehensive US labor statistics through a three-step approach that includes regression and Difference-in-Difference-in-Differences analyses, this study identifies key mechanisms within the labor market that are hidden in aggregated data. Our findings indicate that although the lifting of restrictions resulted in a temporary boost in women's labor force participation, the long-term impacts are still shaped by traditional gender roles. This paper highlights the critical need for policy development that considers gender norms when aiming to increase women's labor force participation and foster a genuine "she-covery".

Keywords: she-cession, she-covery, Claudia Goldin, social reproduction, pandemic restrictions, Difference-in-Difference-in-Differences, labor force participation.

*We extend our deepest gratitude to our supervisor, Sanna Bergvall, for your invaluable assistance and encouragement. We truly appreciate your devotion to our project. Most importantly, we will carry with us the insights gained from your expertise in our shared research interest in gender equality.

*Department of Economics, School of Business, Economics, and Law.

Contents

Figures

Tables

Chapter 1

Introduction

Two primary factors made the SARS-CoV-2 (COVID-19) pandemic the first recession in history to disproportionately affect women, rather than men, in terms of job losses. First, the implementation of social distancing and lockdown measures led to layoffs primarily in sectors predominantly staffed by women (Goldin 2022b; Mohapatra 2021). Second, the widespread closure of schools, nurseries and daycare centers shifted a significant amount of childcare responsibilities into the homes, thereby increasing the demand for unpaid domestic labor (Heintz et al. 2021). These two factors are the reasons why the pandemic is remembered as a “she-cession” (Goldin 2022b).

Previous studies find that women with college degrees were somewhat shielded from job losses, since they were employed in sectors less affected by pandemic restrictions or had opportunities to work from home (Goldin 2022b; Adams-Prassl et al. 2022). However, despite these advantages, approximately 5.1 million women in the United States (US) were still forced to leave the workforce to care for their children (CDC 2023b). During the initial reopening from May to August 2020, men returned to work faster than women (Kim et al. 2022). By May 2021, about 1.3 million women remained out of the workforce, marking the lowest participation rate since 1986 (CDC 2023b). When the mitigation measures were lifted in June 2022, only 58.1% of women aged 20 years and older were participating in the labor force, still 1.2 percentage points lower than the pre-pandemic levels (U.S. Bureau of Labor Statistics 2023). In the post-pandemic era, where COVID-19 restrictions have been lifted, we might expect a labor market recovery for women. However, recovering from a situation marked by reinforced traditional gender roles, which dictate that the increased burden of household labor falls mainly on women (Zhang et al. 2024), may not be as straightforward as it seems.

In this paper, we document changes in women’s labor force participation rates in the post-pandemic period. We employ a three-step analysis approach to examine the entire pandemic period up to the present time and compare it with preceding, more typical years. The first step replicates the study conducted by Goldin (2022b), identifying the groups of women in the US unequally affected by job losses at the onset of the pandemic. Secondly, we extend Goldin’s analysis to include a later time period and shift our focus to examine the dynamics of entering the labor force across genders following the end of COVID-19 restrictions. We focus on the prime-working-age population initially out of the labor force and compare the outcomes with those of pre-pandemic years. In our final step, we conduct Difference-in-Difference-in-Differences (DDD) analyses. This method enables us to compare different groups of women, focusing on how gender roles within households, following the lifting of the final pandemic restrictions, affect women's likelihood of entering the labor force.

Our results reveal that the lifting of pandemic restrictions positively affected the likelihood of both men and women entering the labor force, with an even greater effect for women. However, this additional positive impact distinguishing women from men did not persist as a long-term pattern. Additionally, our findings suggest that the typical negative impact on women's likelihood of entering the labor force, relative to men, is reinforced by both childcare responsibilities and pre-existing gender inequalities among different segments of the prime-working-age population. Our extended analysis further shows that household gender roles influence labor force participation, with single women experiencing a less pronounced negative effect compared to their married counterparts. This variation becomes even more evident from our DDD analyses, which highlight the persistence of restrictive gender norms post-pandemic. These results may suggest an intensification, or at least a more visible manifestation, of traditional gender roles that discourage married women living with their husbands from participating in the labor force.

The results presented in this paper align with previous literature. Following the lifting of COVID-19 restrictions, we should expect a labor market recovery for women, who were unequally affected by job losses (Goldin 2022b). In a post-pandemic era, we might even observe an increased labor force participation rate among women, facilitated by remote work opportunities that allow for a balance between work and family obligations. However, there is a concern that this increase may only be short-term (ibid.). The reason why long-term labor market patterns may diverge could be attributed to the reinforced and intensified traditional gender roles within households (Kabeer et al. 2021; Kevane et al. 2024).

The COVID-19 pandemic serves as a practical illustration of the social reproduction theory (SRT), which posits that the increased demand for household labor during the pandemic primarily falls on women, thereby reinforcing traditional gender norms that are reproduced through continuous practice (Laslett and Brenner 1989). This paper contributes to filling the literature gap on how women's labor market patterns are shaped by gender roles within households in a post-pandemic era. Our study highlights that to successfully increase female labor force participation rates among the prime-working-age population, policies must consider gender norms. To do so, we must go beyond aggregated data and focus on gender differences across sociodemographic groups.

1.1 Background

The background section presents the different time periods relevant to our three-step analysis, and explains the gradual lifting of COVID-19 restrictions which results in our proxy for the end of restrictions and the onset of the post-pandemic period.

The pre-pandemic period, from January 2018 to February 2020, is referred to as the "counterfactual" throughout this paper. This time frame is used to simulate a hypothetical labor market scenario that might have existed if the pandemic had not occurred (Goldin 2022b). The counterfactual allows us to account for regular fluctuations in the labor market, including seasonal variations and provides a baseline for estimating the pandemic's impact on the labor market (ibid.).

In this paper, we define the pandemic period, marked by mitigation measures, as spanning from March 2020, when the World Health Organization declared COVID-19 a global pandemic (CDC 2023b), to June 2022. During this period, restrictions were periodically lifted and reinstated. Throughout the first half of 2022, these measures were systematically removed in the US (Our World in Data 2023). By February 2022, all mandates restricting public gatherings had been lifted. In March, school closures shifted from mandatory to recommended. By April, stay-at-home orders were completely lifted, and by May, mandatory cancellations of public events had ceased. This progression reflected a trend toward returning to normalcy (ibid.). By June 2022, there were no longer any mandates requiring a negative COVID-19 test for entering the country (CDC 2023a).

Figure 1.1 illustrates the Stringency Index[1] between 2020 and 2022, providing a visual representation of the gradual relaxation of the COVID-19 restrictions.

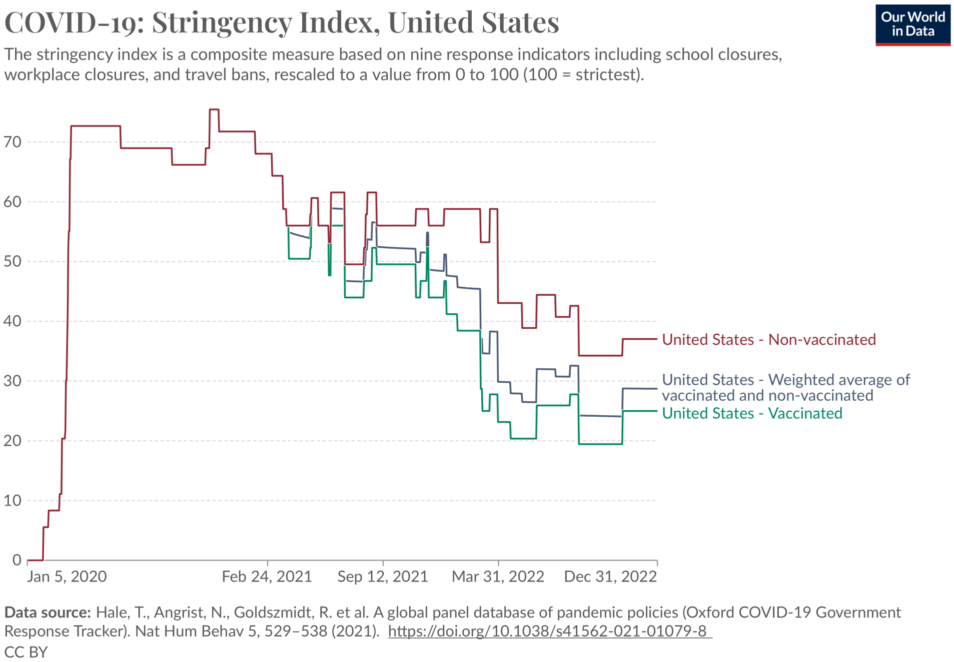

Figure 1.1: The Stringency Index between January 2020 and December 2022 based on three different vaccination statuses.

As shown in Figure 1.1, the middle of 2022 marks a significant point in the US pandemic's downgrade of restrictions. Initially, regulations were applied uniformly regardless of the vaccination status, but from June 2022, the path diverged, with fewer restrictions on vaccinated individuals.

Given this development, June 2022 is assumed to be the most plausible marker for the end of the COVID-19 restrictions in this paper. This date serves as a proxy to assess the impact of the end of pandemic restrictions on the labor market. By choosing June 2022, we also account for factors such as the peak of Omicron between December 2021 and March 2022, as well as potential lagged effects on workforce participation recovery. Consequently, the post-pandemic period is considered to start in June 2022 and extends to the latest available data in February 2024, allowing for an evaluation of the post-pandemic effects on the labor market.

[1] The Stringency Index measures how strict the US's policies are in response to the pandemic, including school and workplace closures, public event cancellations and travel restrictions (Our World in Data 2023). Each restriction is scored from 0 to 100, and the average of these scores gives the daily index value. A higher score means stricter policies. If policies differ between states within the US, the index shows the strictest policy in place (ibid.).

Chapter 2

Social reproduction theory

The mitigation measures implemented by the US government to hinder the spread of the COVID-19 pandemic triggered a social reproduction crisis (Mezzadri et al. 2022). The mass closure of schools, nurseries and daycare centers significantly increased the demand for unpaid domestic labor (Heintz et al. 2021). The social reproduction theory (SRT) provides a framework for understanding the gender-related mechanisms that influence the supply of unpaid domestic labor.

Building on Marx's (1885) analysis of capitalism, which underscores the critical role of labor force continuity in sustaining the economic system, feminist scholars like Laslett and Brenner (1989) have further developed these ideas (Bhattacharya and Vogel 2017). While Marx focused on the necessity of regenerating the worker population for the ongoing production of commodities in a capitalist society, feminist extensions of his work highlight the essential labor *behind* this process, referred to as social reproduction. This involves domestic and care work, including activities such as preparing food, providing clothing, maintaining shelter for immediate consumption, caring for and socializing children, and providing informal care for the elderly (Laslett and Brenner 1989). Scholars of this theory point out that the provision of domestic labor is predominantly undertaken by women, due to gender norms that expect women to prioritize unpaid over paid labor (Bhattacharya and Vogel 2017). The continual engagement of women in household labor contributes to the perpetuation of gender inequality (ibid.).

The pandemic reemphasized the importance of households in providing welfare and enhanced the visibility of social reproduction (Stevano et al. 2021). In times of crisis, the government has the capability to influence gender norms of social reproduction and potentially reduce gender inequality by implementing various austerity measures (Himmelweit 2017). However, it is evident that the austerity measures introduced during the COVID-19 pandemic reinforced rather than reduced traditional gender roles, keeping women out of the labor force (Kabeer et al. 2021; Kevane et al. 2024). If a crisis exacerbates traditional gender stereotypes, the aftermath could both solidify and amplify these norms, leading to a new "old" normal (Anderson 2015, pp. 28–49).

This paper builds on social reproduction theory, which asserts that unpaid labor is primary undertaken by women due to gender norms and is reinforced through continuous practice. Following the increased demand for household labor, we hypothesize that these reinforced traditional gender roles within households are constraining factors in women's labor market recovery post-pandemic.

Chapter 3

Literature review

There is a large body of literature on the labor market impacts of COVID-19. This thesis builds upon those studies that specifically address the consequences of the pandemic, which may explain the potentially persistent effects on women's labor market recovery.

3.1 The she-cession

The COVID-19 pandemic has uniquely impacted the labor market, affecting employment across genders in ways not seen in previous recessions (Goldin 2022b; Hauzel and Pattnaik 2023). Historically, in the US, recessions have typically hit male-dominated sectors like manufacturing and construction hardest, resulting in greater job losses for men compared to women. Conversely, sectors with higher female employment, such as education and health care, have shown more resilience. However, the COVID-19 crisis has diverged from this pattern, targeting industries with substantial female employment due to the demands of social distancing and other lockdown measures. For instance, sectors like hospitality, tourism, entertainment and retail sales, which were less affected in past downturns, have experienced significant job losses, disproportionately affecting women (Goldin 2022b; Mohapatra 2021; Heintz et al. 2021; Bredemeier et al. 2023; Kabeer et al. 2021; Holder et al. 2021).

On the other hand, Goldin (2022b) highlights that the differences in labor market outcomes between men and women during the pandemic were not as large as portrayed in the media. Goldin finds that the greatest disparities occurred not simply between genders but among various sociodemographic groups of women. The most affected were women without college degrees, single mothers to young children, Black and Hispanic women, and older daughters providing care for their aging parents (ibid.).

The impact of the COVID-19 pandemic on job losses for women was not only because they were overrepresented in sectors affected by lockdowns and social restrictions, but also due to the widespread shutdown of schools, nurseries and daycare facilities (Heintz et al. 2021). In the US, parents experienced a significant increase in child-rearing duties, and only approximately one percent of the parents reported that they shared childcare and household chores evenly (Carlson et al. 2021). This small proportion of parents managing equal childcare during the pandemic could be explained by the high number of women employed in essential in-person professions, leading to fathers staying home to care for the children. This suggests that partners may have acted as shock absorbers, somewhat protecting these women from the increased childcare burden, rather than serving as labor-market insurance in case of job loss (Kim et al. 2022). Typically, lower-income women are more likely to rely on extended-family networks for caregiving than other demographic groups (Peek and Fothergill 2008). When crisis make these networks inaccessible, these women are more likely to be hurt (ibid.).

However, regardless of their labor market status or professional commitments, it is clear that mothers spent more time than fathers on childcare during the pandemic (Mohapatra 2021; Moos 2021; Farré et al. 2022; Hauzel and Pattnaik 2023). Previous literature states that working mothers managed to balance their employment with childcare in a manner similar to their unemployed husbands, but unemployed mothers doubled their childcare time compared to their employed counterparts. Consequently, the disruption in women's paid work has been more substantial, with men experiencing nearly twice as many uninterrupted work hours (ibid.). This has led to a widening gap between men and women in total hours worked, including both paid and unpaid labor (Hauzel and Pattnaik 2023). This unequal division of unpaid work between the genders has forced women to exit the labor market, leading to economic insecurity, with effects observed in both the short and long term (Hauzel and Pattnaik 2023; Kabeer et al. 2021).

Hauzel and Pattnaik (2023) argue that the reasons why women primarily take on the caregiving responsibilities are due to the tendency for women's jobs to be undervalued and precarious as well as traditional gender norms. Women occupy part-time or lower-paying positions to a greater extent than men. Therefore, during economic downturns, it becomes economically viable to reduce women's paid work rather than men's, making women more likely to take on unpaid caregiving roles (ibid.). However, other researchers have explored deeper mechanisms behind this disparity, finding that economic incentives do not always determine employment outcomes within families (Correll et al. 2007). For instance, the gendered cultural model of the male breadwinner may lead employers to favor fathers over other workers in employment decisions, including whom to lay off during economic downturns. The gendered cultural model of men as breadwinners and women as caregivers also explains gender stereotypes which lay the framework for traditional gender norms that dictate the roles and behaviors expected of each gender within a household (Zhang et al. 2024). These traditional gender norms played a significant role in the disproportionately increased unpaid domestic work that fell on women during the pandemic (Hauzel and Pattnaik 2023).

3.2 The post-pandemic era

The she-cession has clearly highlighted the role of women as agents of change as we transition from the COVID-19 period to the post-pandemic era (Mohapatra 2021). Previous studies emphasize the importance of recovery policies and political responses that focus on social reproduction and its critical role in sustaining work and life (Kabeer et al. 2021; Kevane et al. 2024). Social and gender norms, along with new internalized behaviors and the distribution of care work within households, significantly influence the efficiency of economic recovery after the pandemic (Kevane et al. 2024). According to Moos (2021), while the US federal government has provided short-term economic assistance in response to COVID-19, it has failed to address the long-term needs for social reproduction. The government has neglected the increasing responsibility for socially reproductive work that households, particularly those headed by women, must manage.

The increased fundamental role of unpaid care during the pandemic has adversely affected women's labor market patterns, leading to both losses of permanent jobs and diminished future economic performance by disrupting their investments in human capabilities (Lafuente et al. 2022; Heintz et al. 2021). In the Spanish labor market, Lafuente et al. (2022) find that mothers have suffered relatively larger losses of high-duration jobs since the pandemic began, more so than men or women without children. These losses emerged approximately one year after the onset of the pandemic and persist, despite a recovery in the aggregate male and female employment rates. Their results highlight potential labor market scars, particularly for mothers, which are obscured by standard employment statistics. These findings indicate that mothers continue to face labor market challenges stemming from the pandemic into late 2022 (ibid.). Additionally, job losses have not only been a temporary setback for those affected during the pandemic but have also led to long-term implications for career progression and future earnings, exacerbating gender inequality (Heintz et al. 2021; Moos 2021). Moreover, since women generally earn less and accumulate less wealth than men, the impact of job loss has been more pronounced for them (Hauzel and Pattnaik 2023).

However, in a post-pandemic era, studies by Arntz et al. (2022) and Goldin (2022b) suggest that the higher acceptance and availability of working from home (WfH) provide opportunities for mothers to increase their working hours and earnings and for fathers to dedicate more time to childcare. This shift can help reduce gender gaps in wages and promotions by more evenly distributing childcare responsibilities within the household, thereby diminishing the so-called "child penalty" (Hauzel and Pattnaik 2023; Arntz et al. 2022). The child penalty refers to the average percentage by which women's earnings fall behind men's five to ten years after the arrival of the first child (Kleven et al. 2019). In the US, this long-term child penalty accounts for more than two-thirds of the overall gender earnings gap (Cortés and Pan 2023). Therefore, the potential for higher WfH rates in a post-pandemic world suggests an increase in gender equality (Hauzel and Pattnaik 2023).

On the other hand, after the increase in WfH rates post-pandemic, previous literature highlights gender disparities among parents. While mothers are more likely to work remotely to balance work and family obligations, fathers tend to use remote work primarily for its comfort (Hauzel and Pattnaik 2023). Moreover, although studies indicate a decrease in the gaps in both working hours and monthly salary between mothers and fathers post-WfH adoption, increases in hourly pay are predominantly observed for fathers (Arntz et al. 2022).

Additionally, while previously introduced flexible work arrangements were initially thought to benefit mothers, they have also reinforced traditional gender norms (Hauzel and Pattnaik 2023). For instance, laws promoting paternity leave and part-time jobs, intended to aid women's employment, have inadvertently hindered their career growth and reduced their pay, especially since women utilize these options more frequently than men. This suggests that the new normal of flexible working hours and remote work opportunities in a post-pandemic era might further widen the gender wage and advancement gaps (ibid.). As Goldin (2022b) argues, although WfH arrangements and increased flexibility can offer part-time opportunities that benefit women in the short term, there are concerns about their long-term efficacy. The full impact of these trends on gender equality in the workplace remains to be seen (ibid.).

This paper makes three important contributions to the existing literature. First, it successfully replicates the study conducted by Goldin (2022b), confirming the findings and demonstrating the effectiveness of her method. This builds trust in the accuracy of the additional analyses presented in this study. Second, this paper is among the first to examine the evolution of women's labor force participation in the aftermath of the atypical event of COVID-19. It particularly focuses on how the transition back to a new normal has been influenced by the significant increase in unpaid domestic labor for women, thereby disrupting their employment development. In the US, such disruption is typically associated with childbirth, but now extends to broader labor market challenges, where the child penalty already accounts for two-thirds of economic gender inequality (Cortés and Pan 2023). Third, this paper goes beyond aggregated data by focusing on differences across sociodemographic groups to uncover lingering effects that can be explained by traditional gender norms, which according to theory may have been intensified during the pandemic.

Chapter 4

Data and methodology

This chapter begins by describing how the data sample was constructed, followed by a discussion about the creation of the counterfactual, and concludes with an explanation of the three-step methodology applied. The first step replicates the regression analysis conducted by Goldin (2022b). The second step extends this analysis to include a later time period using a similar regression approach. The final step builds on the findings from the regression analyses by conducting various of DDD analyses.

4.1 Data sample

The analysis utilizes longitudinal microdata from the Current Population Survey (CPS), provided by the Integrated Public Use Microdata Series (IPUMS), the primary source for US labor market statistics (Flood et al. 2023)[2]. The extracted dataset spans from January 2018 to February 2024 and includes the prime-working-age population, aged between 20 and 54. The CPS uses a rotating panel design, in which individuals are surveyed for four consecutive months, take an eight-month break, and then are surveyed again for four months. By taking advantage of this unique rotating structure, we construct yearly employment flows following the methodology established by Madrian and Lefgren (2000), matching monthly observations of individuals through unique identifiers. To ensure data accuracy, we use the IPUMS validation file, which checks for consistency in age, sex and race to verify that each individual has been interviewed at least once in each of two consecutive years. Those who do not meet these validation criteria are excluded. This dataset forms the basis for all data samples used in our three-step analysis approach. The following sections will detail the creation of each subsample for every step of the analysis.

4.2 Counterfactual

To estimate the impact of the COVID-19 pandemic on the labor market, we compare labor market outcomes during the pandemic with those from a more typical period. The difference in outcomes provides a measure of the pandemic's impact. Identifying the optimal years that best represent typical conditions requires

[2]The data is publicly accessible and does not contain information identifying specific individuals or households. It fulfills ethical standards for research, and we follow ethical guidelines by IPUMS when handling the data.

careful consideration. For instance, failing to account for variations in seasonal fluctuations could skew the results (Kim et al. 2022). Previous literature, exploring employment rates from 2017 to 2019, discovers pronounced gender-specific monthly variations in employment status. Particularly notable was the substantial decline in employment among women, but not men, during the summer months (ibid.). Failing to account for such differences could result in an overestimation of the relative decrease in employment participation due to the pandemic and an underestimation of the increase in labor force participation following the lifting of pandemic restrictions.

For this study, the most reasonable counterfactual is the one conducted by Goldin (2022b). Goldin argues that the most credible approximation of labor market activities in the absence of the pandemic is derived from preceding, more normative years. Goldin highlights that there was an atypical increase in women's labor force participation from late fall 2019 to early winter 2020, just before the pandemic began.[3] The demographics of these women are presented in the following Table 4.1.

Table 4.1: Characteristics of women entering the labor force between April 2019 and February 2020 compared to those always in the labor force.

	Women age 20-54	
	Group 1 *Entered the labor force from April 2019 to February 2020 and remained in to March 2020*	*Group 2* *Always in the labor force when observed from April 2019 to February 2020*
College graduates	0.332	0.467
With no children	0.458	0.447
With children under age 5	0.213	0.152
With children age 5-14	0.197	0.228
Ages 20-29	0.338	0.225
Left labor force March 2020 to last month observed	0.347	0.082
Number of observations	1,834	30,229

† This table is replicated from Goldin (2022b). The data creation for this table is described in Appendix A.

Table 4.1 shows that the group of women who entered the labor force just before the pandemic began includes a higher proportion of younger, less educated women, and mothers with children under the age of five. Additionally, it was

[3] In contrast, men's labor force participation rates did not show a corresponding increase. Instead, there has been a consistent decline each year since the 1960s (Goldin 2022b).

primarily these women who left the labor force more significantly at the onset of the pandemic.[4]

These findings demonstrate that not only can an increased aggregate level of women entering the labor force skew the results, but also that examining different groups of women can lead to even more distorted outcomes if the counterfactual used does not accurately represent a more typical year.

To address this issue, Goldin (2022b) excludes women who entered the labor force between April 2019 and February 2020 by including only those reported to be employed during their initial interview from January 2018 to February 2019. Consequently, this approach allows Goldin to avoid the impact of the large and unusual increase in labor force participation among women during the counterfactual period.

However, when extending Goldin's analysis, we restrict our sample to include only women who reported being out of the labor force during their initial interview between January 2018 and February 2019. We then measure the change in entry rates one year later, from January 2019 to February 2020. This approach thus captures the atypical increase in labor force participation, which could influence our results by underestimating the negative effect of being a woman on the likelihood of entering the labor force. To address this, we conduct a robustness test by estimating the extended regression analysis Equation 4.2 using an earlier time period as the counterfactual. At both the aggregated level of the female population and the subgroup level of women with young children, the magnitude of the coefficients for these dummies only slightly differed from the results presented in chapter 5 and is available upon request.

After careful consideration of whether the time period used by Goldin (2022b) in her counterfactual is suitable for the extended analysis, we have decided to use the same time period. Additionally, in our DDD analyses, this issue does not arise since the counterfactual period only extends from January 2018 to November 2018, thus excluding the 2019 period.

4.3 Replicated regression analysis

The first step in our three-step analysis approach is to replicate the pooled ordinary least squares (OLS) regression Equation 4.1 conducted by Goldin (2022b). We explore variations in employment status by comparing data from one month in one year to the same month in the following year.[5] The counterfactual period, (termed *pre-pre*) includes individuals first interviewed for four consecutive months from

[4]The findings presented in Table 4.1 slightly differ from those reported by Goldin (2022b). These variations can be attributed to differences in sample sizes, which occur because our replication is based solely on the working paper of Goldin (2022a) and we did not have access to the final datasets or scripts.

[5]To track the employment status of women from one year to the next, we construct individual linkages by month across the years of interest. This method is used only for constructing the dependent variable. For the independent variables, we use the first observation from the initial year, assumed to be time-invariant over the year, except for changes in age.

January 2018 to February 2019, with follow-up interviews between January 2019 and February 2020. For the transition into the pandemic, termed *pre-pan*, individuals are initially interviewed between March 2019 and February 2020, followed by subsequent interviews between March 2020 and February 2021. The last period, (*pan-pan*), tracks individuals from their first observations sometime between March 2020 and November 2020 to the following year, from March 2021 to November 2021.

$$
\begin{aligned}
(y^m_{i,t} - y^m_{i,t+1}) &= \Delta y^m_{i,t} \\
&= \alpha + \sum_{\phi=1}^{2} [\beta \times I(\phi)] + \gamma I_{i,t}(C) + \delta I_i(E) \\
&\quad + \theta I_{i,t}(O) + \rho I_i(R) + \mu I_{i,t}(M) \\
&\quad + \eta I_i(X) + \lambda + \kappa + \epsilon_{i,t}
\end{aligned}
\tag{4.1}
$$

The dependent variable Δy represents the change in "at work" status for individual i from its first observation in month m for year t, to the same month in the following year $(t+1)$. The sample is restricted to women who reported being at work during their initial observation (t). The outcome variable equals 1 if the woman is at work in $t+1$, and 0 otherwise. At work includes anyone engaged in any form of paid work during the preceding week (Flood et al. 2023). Excluded from the sample are individuals who have a job but could not work due to illness, housework, or being out of the labor force (ibid.).

The coefficient β measures the effect of each pandemic phase (*pre-pan* and *pan-pan*) φ, relative to the counterfactual period (*pre-pre*). Independent variables, including the age of the youngest child C, education level E, race R, service occupation[6] O and marital status M, are interacted with the pandemic phases, as is the interaction between marital status and a youngest child under age five. The variable X includes a series of indicators that categorize an individual's age into five-year bins, λ comprises a set of annual dummy variables, and κ includes dummy variables for different seasons.

In the context of the linear probability model (LPM) Equation 4.1, the coefficient of an independent variable represents the change in the probability of a woman remaining at work, associated with a one-unit change in that variable while holding all other factors constant. Thus, positive and statistically significant coefficients indicate an increased probability of staying at work, while negative and statistically significant coefficients suggest a decreased likelihood. The interaction terms provide a robust methodology for analyzing the underlying mechanisms of employment status by examining how the effect of one variable on the probability of remaining at work varies with the level of another variable. Specifically, the

[6]The independent variable for service occupation encompasses industries that were heavily impacted by the pandemic's onset, as identified by Goldin (2022b). These sectors include restaurants, bars, barber shops, beauty and nail salons, and other personal care services such as hairdressing and manicuring. Additionally, roles in food preparation, theater attendance, childcare, personal care assistance, fitness instruction, retail sales and home health care are also included (ibid.).

coefficients of the interaction terms measure the extent to which the effect of the main variable deviates from its baseline effect in the reference group under the specified conditions of the interaction term (Stock and Watson 2015).

Given that the same individuals are interviewed multiple times in our sample, their responses are likely to be correlated (Cameron and Trivedi 2006, p. 830). To address this within-group correlation, we employ clustered standard errors (CSE) at the individual level. Additionally, in the context of household surveys, different households may exhibit varying probabilities of inclusion in the sample (ibid.). To ensure our analysis accurately reflects the overall population, and not just the sampled individuals, we incorporate population weights provided by the CPS into Equation 4.1.[7]

4.4 Extended regression analysis

The second step in our three-step analysis extends the replicated regression analysis by including a later time period to estimate the effects of the easing of COVID-19 restrictions and the post-pandemic period on labor market outcomes. We examine variations in labor force participation status from one month in one year to the same month in the next year for both men and women.[8] We use the same years for the counterfactual period (*pre-pre*), but the periods for the pandemic phases differ from those in the replicated regression. For the transition from pandemic restrictions to their final easing (termed *pan-post*), individuals are initially interviewed between March 2020 and May 2022, with follow-up interviews from March 2021 to May 2023. This period allows us to estimate the effect of the gradual lifting of stringent mitigation restrictions, as presented in section 1.1, on the likelihood that individuals enter labor force. The third period, (termed *post-post*), tracks individuals from their initial interviews between June 2022 and February 2023 to their follow-up interviews between June 2023 and February 2024.

[7]Since it is unclear whether Goldin (2022b) applies individual CSE or population weights in her analysis, we initially estimated Equation 4.1 without these adjustments. Including these methods brought our results closer to those reported by Goldin, suggesting she might have used a similar methodology. Results are available upon request.

[8]To track the labor force participation status of individuals from one year to the next, we employ the same methodology for constructing individual linkages for the dependent variable as used in the replicated regression analysis.

To explore changes in labor force participation status across these periods, we estimate the extended regression Equation 4.2.

$$
\begin{aligned}
(L_{i,t}^{m} - L_{i,t+1}^{m}) &= \Delta L_{i,t}^{m} \\
&= \alpha + \sum_{\phi=1}^{2}[\beta \times I(\phi)] + \psi I_{i,t}(F) + \gamma I_{i,t}(C) + \delta I_i(E) \\
&\quad + \theta I_{i,t}(O) + \rho I_i(R) + \mu I_{i,t}(M) \\
&\quad + \eta I_i(X) + \lambda + \kappa + \epsilon_{i,t}
\end{aligned}
\tag{4.2}
$$

One difference between Equation 4.1 and Equation 4.2 is that the dependent variable ΔL represents the change in labor force participation status, and not employment status, between individual i's observation in month m of year t and the same month in year $(t+1)$. Unlike the replicated regression analysis, which only includes individuals who were at work in their initial observation, the extended regression restricts the sample to those initially out of the labor force. This approach allows us to track those who enter the labor force during and after the pandemic. Although we cannot definitively know whether the individuals exited the labor force because of the pandemic itself, using a similar methodology as in the replicated regression analysis enables us to observe outcomes among similar sociodemographic groups of women who left work at the onset of the pandemic. The outcome variable equals 1 if the individual is in the labor force in $t+1$, and 0 otherwise.

The reason why we focus on changes in labor force participation rather than employment status is to better understand the long-term labor market effects of the pandemic. This approach captures individuals who are unemployed and not actively looking for work, instead of those temporarily out of work due to illness or layoffs (Flood et al. 2023). Labor force participation includes individuals who are employed, on leave (due to vacation or illness), actively seeking work or temporarily laid off (ibid.). Therefore, it more accurately reflects the propensity of people to exit the labor force, a dynamic hidden within the at work variable. Given the shifts in WfH opportunities and household dynamics after the pandemic, changes in both the inability to find work or the desire to remain unemployed are captured by examining labor force participation. To contribute to research on the new normal in the labor market post-pandemic, changing the dependent variable is crucial for a more precise examination of the population group we aim to study.

Another difference between the replicated and the extended regression analyses is that Equation 4.2 includes both men and women. The reason for this is to isolate the underlying mechanisms that drive labor force entry rates associated with gender inequalities and norms. The independent variables (C, E, O, R, M) are initially interacted with a female dummy variable F, and subsequently with the phases of the pandemic. The variable X represents a set of indicators categorizing individual ages into five-year intervals, λ includes a series of year dummy variables, and κ consists of seasonal indicators. Similar to Equation 4.1, the coefficient

β in the extended model captures the impact of each of the pandemic phases φ relative to the counterfactual. Moreover, we continue to CSE at the individual level and apply population weights.

Furthermore, the positive and statistically significant coefficients in the LPM Equation 4.2 indicate an increased probability of entering the labor force, while negative and statistically significant coefficients suggest a decreased likelihood. The interaction terms reveal how the effect of a particular variable on the probability of entering the labor force changes depending on the level of another variable.

To understand the population examined, the means of the independent variables for both the restricted and the total data samples are presented in Table 4.2.

Table 4.2: The mean values of the independent variables in the total CPS sample versus the subsample used in the extended regression analysis.

Independent variables	*Means of total CPS sample*	*Means of restricted sample for the extended regression analysis*	*Mean differences*
Female	0.5152	0.6752	-0.1600***
Respondent's age			
20-24	0.0481	0.1568	-0.1086***
25-29	0.0498	0.1129	-0.0632***
30-34	0.0595	0.1347	-0.0751***
35-39	0.0638	0.1420	-0.0782***
40-44	0.0620	0.1357	-0.0737***
45-49	0.0635	0.1402	-0.0767***
>50	0.4265	0.1778	0.2488***
Youngest child's age			
0-4 years	0.0704	0.1819	-0.1115***
5-13 years	0.0902	0.1764	-0.0863***
14-17 year	0.0374	0.0583	-0.0209
18-29	0.0538	0.0626	-0.0089
No residential children	0.7483	0.5212	0.2271***
College graduate	0.2693	0.2311	0.0382
Black	0.0953	0.1140	-0.0188
Hispanic	0.1372	0.1872	-0.0500
Service occupation	0.0540	0.0064	0.0475**
No spouse	0.4925	0.5417	0.0492
Observations	3,622,308	108,530	

† P-Value below 10 %(*); 5 %(**); 1 %(***).

Table 4.2 shows that the restricted data sample, which includes a specific vulnerable demographic of the prime-working-age population who start out of the labor force, contains a higher proportion of women and a lower proportion of college graduates compared to the full dataset. The percentages of Black and Hispanic individuals are somewhat higher, while fewer people work in the service sector. There is also a slightly greater proportion of individuals without a spouse.[9]

4.5 Difference-in-Difference-in-Differences

As the final step in our three-step analysis approach, we aim to estimate the effect of the end of pandemic restrictions on the probability of entering the labor force for various groups of women. The division of groups is based on our goal to investigate how the labor force transition post-pandemic is associated with factors that can help us examine gender norms. We now directly use the individual-level data, pooling all individuals together in a DDD methodology. This approach extends the usual Difference-in-Differences (DD), which estimates the average treatment effect on the treated (ATET) by comparing the variation across time in the differences between outcome means in the control and treatment groups (Stock and Watson 2015, pp. 492–494). First, we explore monthly changes in labor force status between June 2022 and November 2023, using the baseline month of May 2022 as the reference point. This constitutes the first difference. Next, we compare the first difference between the treated group and the counterfactual (the second difference). Lastly, our third difference, which transforms the usual DD method into a DDD estimation, compares the second difference across various groups of women.

The first difference in our analysis involves the treatment variable, which represents the final easing of restrictions in June 2022. Throughout the pandemic, restrictions were removed and reimposed in a staggered fashion across different states and at various times (CDC 2023b). We acknowledge that our treatment does not fully capture the impact of transitioning from full pandemic restrictions to none. However, June 2022 provides the most precise endpoint available for defining this transition.

The second difference is the comparison between women interviewed during the treatment period and those interviewed during the counterfactual period.[10] The validity of the second difference is strongly dependent on the assumption of a common trend between the treatment and control groups (Goodman-Bacon

[9]The mean values of the independent variables for the replicated regression analysis and the DDD analyses are available in Appendix B.

[10]Appendix C provides a graphical overview of the seasonal patterns captured by the counterfactual compared to the patterns during the treatment period. The counterfactual employed in the DDD analysis uses a different time period compared to the regression analyses to match the treatment period. It starts four months prior to the placebo end of restrictions in June 2018, namely February 2018, and extends until 17 months post-placebo, ending in November 2019. Consequently, this selection of counterfactual also avoids the rising trend in women's labor force participation, shown in Table 4.1.

and Marcus 2020). The common trend assumption stipulates that the development of unobservable factors affecting the outcome variable would be similar for both groups in the absence of the treatment (Stock and Watson 2015, p. 492). In this paper, the assumption requires that the difference in the outcome variable only stems from the treatment effect. We are aware that our analysis does not completely satisfy this assumption. However, our primary contribution to research is not to state a causal impact of the easing of pandemic restrictions on women's labor force participation rates, but to describe and document changes in outcomes among different groups of women influenced by gender norms in a post-pandemic era.

For the third difference, we define groups of women based on their marital status, motherhood and educational attainment. We categorize the first group as either never-married or ever-married, based on age differences observed in our data sample. On average, never-married women are in their mid-30s, whereas ever-married women are in their mid-40s. Labor force participation is highest among women who have recently completed their college education and tends to decrease in their 30s and early 40s, often due to childcare responsibilities (Goldin and Mitchell 2017). Participation rates generally increase again after the mid-40s but decline as women move into their 60s (ibid.). Therefore, we separate never-married and ever-married women into two groups to account for these variations in labor force trends over a woman's lifetime in our analysis.

Secondly, we separate married women living with their spouses from the rest of the sample, including married women with absent spouses.[11] This distinction enables us to explore the interaction between women's labor force participation and living in couple households in the context of gender disparities among heterosexual couples. On one hand, previous literature reveals that present spouses functioned as shock absorbers during the pandemic (Carlson et al. 2021). On the other hand, social reproduction theory suggests that women living in couple households are more constrained by traditional gender roles, which may hinder their entry into the labor force.

To investigate how motherhood and educational attainment are associated with women's rate of entering the labor force, we also consider whether women have residential children and whether they have a college degree, in addition to their marital status. This allows us to examine both the impact of school and daycare closures during the COVID-19 pandemic, which forced many parents to educate their children at home, and how the post-pandemic transition to the new normal affects women with various levels of education.

[11] In the CPS data, absent spouses are defined as those institutionalized or living elsewhere for most of the week (Flood et al. 2023).

To analyze how marital, motherhood and education statuses are associated with the effect of the final easing of pandemic restrictions on women's labor force entry rates, we estimate the following DDD model as shown in Equation 4.3:

$$
\begin{aligned}
L_{i,t}^{m} = & \sum_{m,t=\text{Jun, 2022}}^{\text{Nov, 2023}} \beta_t^m M_t^m + \eta C + \sum_{m,t=\text{Jun, 2022}}^{\text{Nov, 2023}} \delta_t^m (M_t^m \times C) + \gamma_g G_g \\
& + \sum_{m,t=\text{Jun, 2022}}^{\text{Nov, 2023}} \omega_{t,g}^m (M_t^m \times G_g) + \theta_g (C \times G_g) \\
& + \sum_{m,t=\text{Jun, 2022}}^{\text{Nov, 2023}} \psi_{t,g}^m (M_t^m \times C \times G_g) + \alpha_i + \epsilon_{i,t}
\end{aligned} \tag{4.3}
$$

In Equation 4.3, the outcome variable L represents the status, not the change, in labor force participation, as in the extended regression Equation 4.2. We change the dependent variable because the DDD framework requires the dependent variable to indicate the timing of the treatment, separating whether the individual has been exposed to it and how far away in time the interview was conducted. However, we restrict the sample in the same way as before, including only individuals who were initially out of the labor force.

In Equation 4.3, M represents a vector of dummy variables for each month and year, distinguishing the period from June 2022 to November 2023 from the baseline month of May 2022. The coefficient β measures the labor force participation rate for each month m and year t, relative to May 2022. C is a dummy indicator that differentiates the treatment and the counterfactual periods. G represents ten different dummy-variable groups that estimate variations based on marital status, motherhood and educational attainment.[12] The main coefficient of interest is ψ. ψ compares the effect of the treated time period (the post-pandemic period) to the control group (the counterfactual) on changes in labor force participation across months (m) and years (t) and facilitates comparisons across each group relative to its counterpart.

Similar to the regression analyses, we apply individual CSE and population weights to Equation 4.3. However, unlike the regression analyses where the dependent variable measures the *change* in employment and labor force particip-

[12]The groups are G_1: ever-married women (never-married women), G_2: women with present spouse (women without present spouse), G_3: ever-married women with child (never-married women without child), G_4: women with present spouse and child (women without present spouse and child), G_5: ever-married women without child (never-married women with child), G_6: women with present spouse, without child (women without present spouse, with child), G_7: ever-married women with college (never-married women with college), G_8: women with present spouse and college (women without present spouse and college), G_9: ever-married women without college (never-married women with college) and G_{10}: women with present spouse without college (women without present spouse with college). Equation 4.3 has also been performed for four additional dummy indicator groups, focusing on interactions between children, education and marital status. These results are presented in Appendix E.

ation statuses between two years, and thereby inherently accounting for unobserved individual-specific characteristics that are constant over time, the dependent variable in Equation 4.3 represents the labor force participation *status*, not the change. Therefore, we control for unobserved and time-invariant individual characteristics, for example intrinsic motivation or personal skills that affect labor force participation status, by including individual-specific fixed effects (FE) (Stock and Watson 2015; Cameron and Trivedi 2006, pp. 361, 9).

Chapter 5

Results and analysis

This chapter presents the findings from our three-step analysis approach. We begin by presenting the results of the replicated regression analysis based on the study conducted by Goldin (2022b). Next, we describe the outcomes of the extended regression analysis. The final section discusses the results from the DDD analyses.

5.1 Replicated regression analysis

In the following Table 5.1, the results from Equation 4.1 are presented.

Table 5.1: Annual changes in at work rates for women between 20 and 54 years from January 2018 to November 2021.

	Women at work in year t, month m			
	Main effects	*Plus child interactions*	*Plus race and occupation interactions*	*Plus marital interactions*
Respondent's age				
20-24	-0.0803^{***}	-0.0804^{***}	-0.0802^{***}	-0.0860^{***}
	(0.006)	(0.006)	(0.006)	(0.006)
25-29	-0.0210^{***}	-0.0211^{***}	-0.0208^{***}	-0.0244^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
30-34	-0.0148^{***}	-0.0147^{***}	-0.0148^{***}	-0.0176^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
35-39	0.0097^{**}	0.0098^{**}	0.0099^{**}	0.0071
	(0.004)	(0.004)	(0.004)	(0.004)
40-44	0.0073^{*}	0.0074^{*}	0.0076^{*}	0.0062
	(0.004)	(0.004)	(0.004)	(0.004)
45-49	0.0091^{**}	0.0091^{**}	0.0092^{**}	0.0086^{**}
	(0.004)	(0.004)	(0.004)	(0.004)
Youngest child's age				
0-4 years	-0.0294^{***}	-0.0183^{***}	-0.0186^{***}	-0.0126^{**}
	(0.004)	(0.005)	(0.005)	(0.006)
5-13 years	-0.0091^{***}	-0.0056	-0.0051	-0.0010
	(0.003)	(0.004)	(0.004)	(0.005)
14-17 years	0.0083^{*}	0.0045	0.0054	0.0089
	(0.004)	(0.006)	(0.006)	(0.006)

Table 5.1 Continued from previous page

Women at work in year t, month m				
	Main effects	*Plus child interactions*	*Plus race and occupation interactions*	*Plus marital interactions*
18-29 years	0.0074	0.0074	0.0085	0.0113*
	(0.005)	(0.006)	(0.006)	(0.006)
College graduate	0.0241***	0.0237***	0.0295***	0.0309***
	(0.003)	(0.003)	(0.003)	(0.003)
Black	−0.0224***	−0.0224***	−0.0138**	−0.0173***
	(0.004)	(0.004)	(0.006)	(0.006)
Hispanic	−0.0299***	−0.0299***	−0.0272***	−0.0282***
	(0.004)	(0.004)	(0.005)	(0.005)
Service occupation	−0.0157***	−0.0157***	0.0139***	0.0131***
	(0.004)	(0.004)	(0.005)	(0.005)
Start year 2018	−0.0289***	−0.0289***	−0.0293***	−0.0293***
	(0.007)	(0.007)	(0.007)	(0.007)
Start year 2019	−0.0335***	−0.0336***	−0.0336***	−0.0337***
	(0.005)	(0.005)	(0.005)	(0.005)
Spring	−0.0185***	−0.0185***	−0.0184***	−0.0185***
	(0.003)	(0.003)	(0.003)	(0.003)
Summer	−0.0235***	−0.0235***	−0.0235***	−0.0238***
	(0.004)	(0.004)	(0.004)	(0.004)
Fall	0.0073**	0.0073**	0.0074**	0.0073**
	(0.003)	(0.003)	(0.003)	(0.003)
Prepandemic to pandemic (pre-pan)	−0.1001*** (0.006)	−0.0942*** (0.007)	−0.0719*** (0.007)	−0.0707*** (0.008)
Pandemic to pandemic (pan-pan)	−0.0429*** (0.008)	−0.0428*** (0.009)	−0.0413*** (0.009)	−0.0391*** (0.010)
Pre-pan × college	0.0573***	0.0579***	0.0423***	0.0405***
	(0.006)	(0.006)	(0.006)	(0.006)
Pan-pan × college	0.0077	0.0082	0.0075	0.0059
	(0.006)	(0.006)	(0.006)	(0.006)
Pre-pan × children under age 5		−0.0254*** (0.009)	−0.0245*** (0.009)	−0.0148 (0.010)
Pan-pan × children under age 5		−0.0098 (0.010)	−0.0097 (0.009)	−0.0020 (0.011)
Pre-pan × children age 5-13		−0.0103 (0.007)	−0.0114 (0.007)	−0.0114 (0.008)
Pan-pan × children age 5-13		0.0004 (0.007)	0.0000 (0.007)	−0.0008 (0.008)
Pre-pan × children age 14-18		0.0052 (0.009)	0.0028 (0.009)	0.0023 (0.010)

Table 5.1 Continued from previous page

	Women at work in year t, month m			
	Main effects	*Plus child interactions*	*Plus race and occupation interactions*	*Plus marital interactions*
Pan-pan × children age 14-18		0.0086 (0.009)	0.0080 (0.009)	0.0069 (0.010)
Pre-pan × children age 18-30		−0.0032 (0.010)	−0.0044 (0.010)	−0.0050 (0.010)
Pan-pan × children age 18-30		0.0045 (0.010)	0.0040 (0.010)	0.0030 (0.010)
Pre-pan × Black			−0.0162* (0.010)	−0.0143 (0.010)
Pan-pan × Black			−0.0133 (0.010)	−0.0113 (0.011)
Pre-pan × Hispanic			−0.0125 (0.009)	−0.0117 (0.009)
Pan-pan × Hispanic			0.0067 (0.009)	0.0075 (0.009)
Pre-pan × service occupation			−0.0832*** (0.009)	−0.0828*** (0.009)
Pan-pan × service occupation			−0.0028 (0.009)	−0.0020 (0.009)
No spouse				0.0155*** (0.004)
Pre-pan × no spouse				−0.0010 (0.006)
Pan-pan × no spouse				−0.0027 (0.007)
Pre-pan × no spouse × children under age 5				−0.0396** (0.017)
Pan-pan × no spouse × children under age 5				−0.0385** (0.019)
Constant	0.9534*** (0.007)	0.9513*** (0.007)	0.9431*** (0.007)	0.9362*** (0.007)
R2	0.0309	0.0310	0.0327	0.0331
Adjusted R2	0.0307	0.0309	0.0325	0.0329
Observations	172, 103	172, 103	172, 103	172, 103

† P-Value below 10 %(*); 5 %(**); 1 %(***) and standard errors in brackets. This table is replicated from the analysis conducted by Goldin (2022b).

The results in Table 5.1 indicate a successful replication of the regression findings in Goldin (2022b), achieving the same directional coefficients with only minor differences in magnitudes and levels of statistical significance. These discrepancies are likely due to differences in sample sizes and arise from conducting the analysis based on the working paper by Goldin (2022a), without access to finalized datasets or scripts. These minor differences suggest that we effectively managed to replicate Goldin's analysis.[13]

Similar to the findings of Goldin (2022b), the results in Table 5.1, column 1, suggest that women with college degrees were relatively protected from job losses during the transition into the pandemic (*pre-pan*), as indicated by the combined effect of the main variable and the interaction term. Specifically, the overall effect of transitioning into the pandemic indicates a decrease in the probability of staying employed by 10.01 percentage points (pp) for women. However, women with college degrees experienced a mitigated reduction, with an extra increase in their likelihood of being at work by 5.73 pp. This suggests that the employment reduction for college-educated women was approximately halved compared to the broader prime-working-age female population in our dataset. Moreover, as the pandemic progressed, the interaction between the pandemic phase (*pan-pan*) and college education did not show any statistically significant additional impact on the likelihood of these women remaining employed. This means that while college degrees offered some initial protection, their impact did not differentiate the effect of the pandemic on employment as it continued.

As shown in column 2 in Table 5.1, the onset of COVID-19 disproportionately affected mothers with children aged zero to four years. Moreover, the findings in column 3 highlight increased employment instability among Black women and those working in service occupations.

Additionally, the only group of women that experienced an extra negative and statistically significant effect on their likelihood of remaining employed during the pandemic were single mothers with children under the age of five, as evidenced by the interaction term with the "no spouse" variable in column 4 in Table 5.1.

[13] As a robustness check, we estimate the regression Equation 4.1 using the change in labor force participation as the dependent variable. The findings, presented in Appendix D, are robust, despite a decrease in magnitude. This decrease aligns with expectations that the number of women reporting not being at work the preceding week is likely higher than the number of women who left the labor force entirely due to the pandemic.

5.2 Extended regression analysis

In Table 5.2, the results from the extended regression Equation 4.2 are presented.

Table 5.2: Annual changes in labor force rates for women and men between 20 and 54 years from January 2018 to February 2024.

Women and men out of the labor force in year t, month m				
	Main effects	*Plus college degree, child, race and occupation interactions*	*Plus female interactions*	*Plus marital interactions*
Female	-0.0683^{***}	-0.0755^{***}	-0.0240	-0.0476^{**}
	(0.011)	(0.012)	(0.015)	(0.023)
Respondent's age				
20-24	0.2119^{***}	0.2120^{***}	0.2167^{***}	0.2184^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
25-29	0.1575^{***}	0.1575^{***}	0.1633^{***}	0.1649^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
30-34	0.1152^{***}	0.1153^{***}	0.1219^{***}	0.1236^{***}
	(0.008)	(0.008)	(0.008)	(0.008)
35-39	0.0740^{***}	0.0741^{***}	0.0804^{***}	0.0815^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
40-44	0.0454^{***}	0.0453^{***}	0.0486^{***}	0.0498^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
45-49	0.0265^{***}	0.0264^{***}	0.0277^{***}	0.0285^{***}
	(0.007)	(0.007)	(0.007)	(0.007)
Youngest child's age				
0-4 years	-0.0009	-0.0113	0.1107^{***}	0.0852^{***}
	(0.007)	(0.011)	(0.031)	(0.032)
5-13 years	0.0492^{***}	0.0355^{***}	0.1125^{***}	0.0895^{***}
	(0.007)	(0.010)	(0.016)	(0.017)
14-17 years	0.0554^{***}	0.0475^{***}	0.0433^{***}	0.0386^{***}
	(0.009)	(0.015)	(0.015)	(0.015)
18-29 years	0.0482^{***}	0.0484^{***}	0.0437^{***}	0.0405^{***}
	(0.008)	(0.014)	(0.014)	(0.014)
College graduate	0.0809^{***}	0.0838^{***}	0.1280^{***}	0.1209^{***}
	(0.005)	(0.009)	(0.02)	(0.02)
Black	0.0271^{***}	0.0123	0.0027	0.0063
	(0.007)	(0.011)	(0.018)	(0.0018)
Hispanic	0.0422^{***}	0.0482^{***}	0.0753^{***}	0.0765^{***}
	(0.005)	(0.009)	(0.019)	(0.019)

Table 5.2 Continued from previous page

Women and men out of the labor force in year t, month m

	Main effects	*Plus college degree, child, race and occupation interactions*	*Plus female interactions*	*Plus marital interactions*
Service occupation	0.2583***	0.2767***	0.2753***	0.2757***
	(0.022)	(0.038)	(0.04)	(0.04)
No spouse	0.0296***	0.0295***	0.0288***	−0.0204
	(0.005)	(0.005)	(0.005)	(0.015)
Start year 2019	0.0029	0.0029	0.0031	0.0033
	(0.008)	(0.008)	(0.008)	(0.008)
Start year 2020	0.0093	0.0095	0.0079	0.0084
	(0.013)	(0.013)	(0.013)	(0.013)
Start year 2021	0.0122	0.0123	0.0122	0.0127
	(0.013)	(0.013)	(0.013)	(0.013)
Start year 2022	0.0011	0.0013	0.0003	0.0007
	(0.01)	(0.01)	(0.01)	(0.01)
Spring	0.0061	0.0062	0.0060	0.0060
	(0.005)	(0.005)	(0.005)	(0.0045)
Summer	0.0132**	0.0132**	0.0136**	0.0135**
	(0.005)	(0.005)	(0.005)	(0.005)
Fall	0.0095**	0.0095**	0.0105**	0.0104**
	(0.005)	(0.005)	(0.005)	(0.005)
Pandemic to post-pandemic (pan-post)	0.0312**	0.0278*	0.0251	0.0218
	(0.015)	(0.015)	(0.016)	(0.021)
Post-pandemic to post-pandemic (post-post)	0.0327**	0.0264*	0.0205	−0.0127*
	(0.014)	(0.015)	(0.016)	(0.026)
Pan-post × female	0.0309**	0.0406***	0.0269	0.0087
	(0.013)	(0.014)	(0.018)	(0.027)
Post-post × female	0.0005	0.0088	0.0024	−0.0173
	(0.012)	(0.013)	(0.017)	(0.026)
Pan-post × college		−0.0108	−0.0385	−0.0388
		(0.012)	(0.025)	(0.025)
Post-post × college		0.0161	0.0413	0.0476
		(0.015)	(0.033)	(0.033)
Pan-post × children under age 5		0.0111	0.0433	0.0469
		(0.013)	(0.039)	(0.040)

Table 5.2 Continued from previous page

Women and men out of the labor force in year t, month m				
	Main effects	*Plus college degree, child, race and occupation interactions*	*Plus female interactions*	*Plus marital interactions*
Post-post × children under age 5		0.0246	−0.0102	0.0111
		(0.018)	(0.052)	(0.054)
Pan-post × children age 5-13		0.0143	0.0134	0.0162
		(0.013)	(0.013)	(0.014)
Post-post × children age 5-13		0.0332*	0.0310*	0.0429**
		(0.017)	(0.017)	(0.018)
Pan-post × children age 14-17		0.0084	0.0081	0.0124
		(0.019)	(0.019)	(0.019)
Post-post × children age 14-17		0.0191	0.0208	0.0337
		(0.025)	(0.025)	(0.026)
Pan-post × children age 18-30		−0.0064	−0.0964	−0.0041
		(0.018)	(0.018)	(0.018)
Post-post × children age 18-30		0.0168	0.0162	0.0278
		(0.023)	(0.023)	(0.024)
Pan-post × Black		0.0236	−0.0112	−0.0121
		(0.014)	(0.023)	(0.023)
Post-post × Black		0.0122	−0.0183	−0.0210
		(0.02)	(0.032)	(0.032)
Pan-post × Hispanic		−0.0046	0.0534**	0.0537**
		(0.012)	(0.025)	(0.025)
Post-post × Hispanic		−0.0203	0.0151	0.0142
		(0.015)	(0.031)	(0.031)
Pan-post × Service occupation		0.0032	0.0173	0.01840
		(0.048)	(0.065)	(0.065)
Post-post × Service occupation		−0.1465***	−0.2695**	−0.2700**
		(0.072)	(0.120)	(0.119)
Female × children under age 5			−0.1450***	−0.1188***
			(0.033)	(0.033)
Female × children age 5-13			−0.0981***	−0.0741***
			(0.015)	(0.033)
Female × College degree			−0.0566**	−0.0479**
			(0.023)	(0.023)
Female × Black			0.0158	0.0100
			(0.023)	(0.023)

Table 5.2 Continued from previous page

Women and men out of the labor force in year t, month m				
	Main effects	*Plus college degree, child, race and occupation interactions*	*Plus female interactions*	*Plus marital interactions*
Female × Hispanic			−0.0359*	−0.0369*
			(0.022)	(0.022)
Female × Service occupation			−0.0140**	−0.0160**
			(0.061)	(0.061)
Female × pan-post × children under age 5			−0.0405	−0.0413
			(0.041)	(0.042)
Female × post-post × children under age 5			0.0342	0.0226
			(0.056)	(0.057)
Female × pan-post × college degree			0.0323	0.0339
			(0.028)	(0.028)
Female × post-post × college degree			−0.0405	−0.0435
			(0.037)	(0.037)
Female × pan-post × Black			0.0580*	0.0568*
			(0.030)	(0.030)
Female × post-post × Black			0.0475	0.0466
			(0.041)	(0.041)
Female × pan-post × Hispanic			−0.0788***	−0.0792***
			(0.028)	(0.028)
Female × post-post × Hispanic			−0.0530	−0.0522
			(0.036)	(0.036)
Female × pan-post × service occupation			−0.0218	−0.0250
			(0.063)	(0.063)
Female × post-post × service occupation			0.1708	0.1670
			(0.135)	(0.134)
Pan-post × no spouse				0.0048
				(0.019)
Post-post × no spouse				0.0422
				(0.026)
Female × no spouse				0.0577***
				(0.017)

Table 5.2 Continued from previous page

Women and men out of the labor force in year t, month m				
	Main effects	*Plus college degree, child, race and occupation interactions*	*Plus female interactions*	*Plus marital interactions*
Female × pan-post × no spouse				0.0014
				(0.022)
Female × post-post × no spouse				−0.0237
				(0.030)
Constant	0.0997***	0.1026***	0.0764***	0.1138***
	(0.009)	(0.009)	(0.010)	(0.014)
R2	0.0411	0.0415	0.0478	0.0484
Adjusted R2	0.0409	0.0411	0.0472	0.0479
Observations	108,530	108,530	108,530	108,530

† P-Value below 10 %(*); 5 %(**); 1 %(***) and standard errors in brackets.

In column 1 in Table 5.2, both the main effects and the interactions between the pandemic phases and the female dummy are presented. Without considering the transition from full pandemic restrictions to the easing of restrictions (*pan-post*) or the post-pandemic period (*post-post*), the results indicate that being a prime-working-age woman is associated with a negative impact on the likelihood of entering the labor force relative to men. During the transition from pandemic restrictions to an easing of restrictions, both men and women experience a positive impact of 3.12 pp on their likelihood of entering the labor force. This corresponds to an effect size of 12.55% compared to the average rate for all individuals entering the labor force.[14] However, following the easing of restrictions, women experience an extra positive and statistically significant effect of 3.09 pp, which is approximately double the positive effect of lifting restrictions compared to men. This aligns with expectations, considering the disproportionate job losses they faced due to lockdowns and social restrictions. The relaxation of these stringent measures subsequently facilitated an increase in women's entry rates into the labor force. Furthermore, during the post-pandemic period, both men and women show a positive impact of 3.27 pp on their likelihood of entering the labor force. However, the interaction term with female in the post-pandemic phase is not statistically significant, and its magnitude is negligible, indicating that we cannot assert any additional positive effect of the post-pandemic period on women's likelihood of entering the labor force relative to men. In summary, the findings from column 1 suggest that while the transition from full pandemic restrictions to

[14]The effect size is calculated by taking the ratio of the coefficient's percentage point change to the mean value of the dependent variable during the same time period.

the easing of restrictions did not translate into a long-term advantage for women relative to men, the end of the pandemic did have positive effects on labor force entry rates for both genders. Nevertheless, it did not counteract the negative impact of being a woman during preceding years on the likelihood of entering the labor force, highlighting persistent pre-existing gender inequalities in the labor market.

Interactions of the pandemic phases with various sociodemographic groups are added in column 2 in Table 5.2. For the post-pandemic period, the overall effect for both men and women is an increase in labor force participation entry rates of 2.64 pp. Additionally, statistically significant extra effects are observed for two specific groups: individuals with children aged five to thirteen, and those employed in the service sector. Parents of children in this age group face an additional positive effect of 3.32 pp on their likelihood of entering the labor force in the post-pandemic period. Conversely, individuals working in the service sector experience an extra negative impact of 14.65 pp. This divergence suggests that service sector workers, who typically have less attachment to the labor market and often hold lower levels of education or belonging to minority groups (Goldin 2022b), face barriers to entering the labor force in the current post-pandemic environment.

When interactions between gender and sociodemographic groups, along with the pandemic phases, are included in the regression analysis, the results in column 3 in Table 5.2 reveal gender inequalities attributed to different segments of the overall prime-working-age population. To begin with, excluding any specific pandemic periods, the effect of having children under the age of five differs between mothers and fathers. Generally, having young children positively influences fathers' likelihood of joining the labor force. Conversely, mothers face an additional negative effect of 14.5 pp on their likelihood of entering the labor force compared to their male counterparts. A similar trend appears for parents with the youngest child aged five to thirteen. Additionally, holding all other variables constant, possessing a college degree increases the likelihood of entering the labor force by 12.8 pp for all individuals. However, this positive effect is reduced by approximately half for women. Moreover, while Hispanic individuals generally have a higher likelihood of entering the labor force, Hispanic women experience an additional negative impact. This effect becomes more pronounced as pandemic restrictions are eased. In summary, the results from column 3 suggest that the negative effect of being a woman on the likelihood of entering the labor force is reinforced by both childcare responsibilities and pre-existing gender inequalities among different sociodemographic groups.

Moreover, the results from columns 1 to 3 in Table 5.2 reveal that, holding other factors constant, being single (as indicated by the no spouse variable) has a positive and statistically significant effect on the likelihood of entering the labor force for both men and women throughout the study period. This implies that single men and women are more likely to enter the labor force than their married counterparts. However, when the interaction term between female and no spouse is introduced in column 4, the impact for men becomes statistically insignificant, with a negligible coefficient magnitude. In contrast, for single women, the additional effect that distinguishes them from single men is statistically significant and positive, amounting to 5.77 pp. This corresponds to an effect size of 24% relative to the average rate of entry into the labor force for the total sample. These findings suggest that women with spouses face a greater negative impact on their probability of entering the labor force compared to those without.[15]

[15] As a robustness test, we performed the regression analysis including a control variable for state-specific variations in Equation 4.2. The results remained consistent and are available upon request.

5.3 Difference-in-Difference-in-Differences

In this section, we graphically present the results from the estimated DDD model Equation 4.3. Although we cannot establish statistical significance or causality using the final easing of pandemic restrictions in June 2022 as a treatment effect on labor force participation rates, we utilize the findings to explore mechanisms that may influence women's labor market patterns post-pandemic.

Figure 5.1 illustrates how the combination of marital status and the presence of children, when interacted with June 2022, influences labor force entry rates for women.

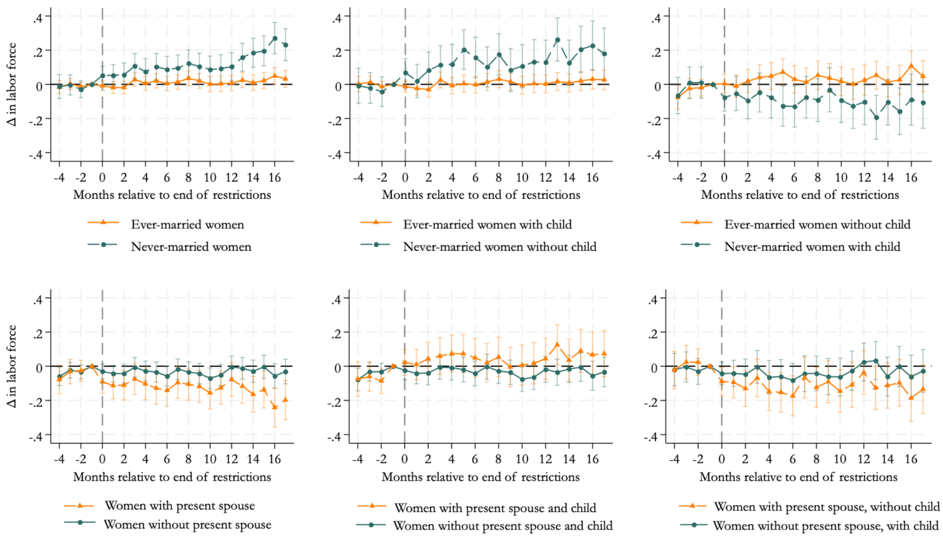

Figure 5.1: DDD analyses of labor force participation entry rates, with June 2022 as the treatment indicator, interacted with marital status and residential children. The analyses control for seasonal variations and individual-specific effects.

†The vertical lines denote 95% confidence intervals. Ever-married women includes those who are currently married, regardless of whether their spouses are present or not, separated, divorced or widowed. Women without present spouses includes those who are currently married with absent spouses, separated, divorced or widowed.

The initial set of charts in Figure 5.1 shows an increase in the likelihood of never-married women entering the labor force after the lifting of COVID-19 restrictions. However, this trend changes when motherhood is introduced. Never-married mothers tend to join the labor force at a lower rate, indicating that the final easing of restrictions did not benefit this subgroup as much as it did their childless counterparts. It is conceivable that an increase in labor force participation among never-married mothers might have emerged earlier, possibly in March or April 2022, following the removal of school closures and stay-at-home orders.

Another potential explanation for the shift from a positive to a negative trend among never-married women when considering motherhood could be that this group predominantly comprises women in their mid-30s, an age when many often reduce their work involvement, typically due to childcare demands (Goldin and Mitchell 2017). For the rest of the women, who are on average in their mid-40s, the presence of children does not appear to influence their likelihood of entering the labor force in the post-pandemic era. This may be because their children are older and require less intensive childcare compared to younger children.

Moving to the second set of charts in Figure 5.1, which examines differences between married women living in couple households and their counterparts, we observe that married women living with their spouses generally show a lower probability of entering the labor force after the pandemic restrictions are eased. Speculatively, this finding suggests that traditional gender roles within couple households tend to keep women out of the labor force. Additionally, when motherhood is considered, the negative trend for these married women shifts slightly positive. This supports previous literature suggesting that during the pandemic, one parent often had to leave the labor force to care for their children, typically the mother (Mohapatra 2021; Moos 2021; Farré et al. 2022; Hauzel and Pattnaik 2023), who is now increasingly entering the labor force as restrictions are lifted.

In Figure 5.2, we illustrate the effects of marital status and educational attainment, interacted with June 2022, on labor force entry rates for women.

Figure 5.2: DDD analyses of labor force participation entry rates, with June 2022 as the treatment indicator, interacted with marital status and education level. The analyses control for seasonal variations and individual-specific effects.

[†]The vertical lines denote 95% confidence intervals. Ever-married women includes those who are currently married, regardless of whether their spouses are present or not, separated, divorced or widowed. Women without present spouses includes those who are currently married with absent spouses, separated, divorced or widowed.

The first row in Figure 5.2 shows that holding a college degree increases the likelihood of the prime-working-age female population entering the labor force after the lifting of restrictions. However, as shown in Figure E.1 in Appendix C, this positive effect diminishes when the presence of children is considered.

Moreover, for married women living with their spouses, possessing a college degree is associated with an increased probability of entering the labor force post-pandemic, highlighting the importance of educational attainment on labor force participation within couple households. This supports existing literature suggesting that women living with their husbands may encounter more constraints from traditional gender roles, especially if they are in lower-paid jobs or temporary positions typically associated with lower educational levels (Hauzel and Pattnaik 2023; Goldin 2022b).

Additionally, as shown in Figure E.1 in Appendix C, the presence of children appears to contradict the positive effect of a college degree for married women in couple households. This could indicate that childcare responsibilities mitigate the beneficial impact of higher education for mothers in couple households. In contrast, having a college degree still increases the likelihood for mothers not living with a partner. These results may suggest that the extended availability of WfH opportunities post-pandemic, typically for college graduates, primarily benefits mothers only if they are not constrained by traditional gender roles within households. This aligns with previous literature expressing concerns that flexible working arrangements may not reduce the child penalty faced by mothers, but rather reinforce traditional gender roles (Hauzel and Pattnaik 2023). In summary, these observations suggest that traditional gender norms continue to play a crucial role in influencing labor market dynamics in the post-pandemic era.

Although the estimated effects in our DDD analyses offer directional insights, they are generally not statistically distinct from one another, and thus, the coefficients should be interpreted with caution. However, the alignment of these effects with expectations provides indicative power and contributes with several suggestions that labor market dynamics post-pandemic are still shaped by traditional gender norms.

Chapter 6

Discussion and concluding remarks

This paper contributes to the literature on the impact of the COVID-19 pandemic on the US labor market by being one of the first to document changes in women's labor market patterns post-pandemic, with a focus on gender norms. We adopt a three-step analysis approach to examine the entire pandemic period up to the present and compare it with preceding, more typical years. The first step replicates the study conducted by Goldin (2022b), identifying groups of women in the US who were disproportionately affected by job losses due to the onset of pandemic restrictions. We then extend Goldin's analysis and include a later time period, shifting our focus to examine the gender-related mechanisms in labor force participation among the prime-working-age population post-pandemic. The extended analysis suggests that pre-existing gender inequalities play a crucial role in determining who enters the labor force and reveal a visible manifestation of traditional gender roles. Building on these insights, we conclude our analysis with the third step: employing Difference-in-Difference-in-Differences (DDD) analyses to examine how the final easing of pandemic restrictions affects the likelihood of entering the labor force for various groups of women, exploring the association with gender norms in the new post-pandemic normal.

The findings in this paper provide several insightful results that align with previous literature and theory. Our results support the notion that the COVID-19 pandemic illustrates how the theory of social reproduction aligns with real-world practices (Mezzadri et al. 2022). This theory suggests that the increased household labor due to the widespread closure of schools, nurseries and daycare centers is primarily undertaken by women (Bhattacharya and Vogel 2017). This is evidenced by the findings from the replicated regression analysis, which show a pronounced negative impact of the pandemic on the likelihood of single mothers remaining employed due to childcare responsibilities. Additionally, our extended analysis reveals that women, to a greater extent than men, increased their likelihood of entering the labor force following the easing of restrictions. This aligns with expectations given the disproportionate job losses women experienced due to the implementation of lockdown and social distancing measures. However, this extra positive impact for women was not long-lasting, supporting concerns from previous literature that an increase in women's labor force participation post-pandemic might not establish a long-term trend (Goldin 2022b).

In the post-pandemic era, previous literature highlights both the advantages and disadvantages of increased opportunities for remote work and flexible schedules for women's participation in the labor market (Arntz et al. 2022; Goldin 2022b). On one hand, these arrangements enable mothers to balance household duties with employment. On the other hand, they make it more challenging for women to achieve career advancements. Additionally, the increased flexibility often leads to greater household labor for women, thereby reinforcing traditional gender roles within households (Hauzel and Pattnaik 2023).

Aligning with our expectations, the results from the DDD analyses indicate that traditional gender norms influence women's likelihood of entering the labor force post-pandemic. For instance, married women living in couple households demonstrate a lower probability of entering the labor force after pandemic restrictions are eased. This becomes even more evident when we consider levels of education and childcare responsibilities in the analysis. The results reveal that the positive effect of having a college degree on the likelihood of participating in the labor force decreases if the woman has childcare obligations and lives with her husband. The persistence of restrictive gender norms post-pandemic suggests a potential intensification, in line with social reproduction theory, possibly causing the labor market to revert to a new "old" normal (Anderson 2015; Bhattacharya and Vogel 2017, pp. 28–49).

Our results highlight the importance of centering labor market policies around social reproduction (Kevane et al. 2024; Kabeer et al. 2021). Previous studies have shown that while paternity leave and part-time employment can increase women's labor force participation, these resources are more frequently used by women than men, widening the earnings and career advancement gaps between the genders (Kevane et al. 2024; Kabeer et al. 2021). This underscores the fact that policies intended to benefit women do not always provide the intended outcomes due to entrenched gender norms. As we navigate a new normal with potentially enhanced traditional gender roles, it becomes clear that family-friendly policies, which often lead women to take on childcare obligations, may not benefit women in couple households in the long term. These policies tend to perpetuate traditional gender roles that dictate who assumes these responsibilities. Therefore, it is crucial that gender norms are carefully considered when developing policies aimed at enhancing women's labor force participation.

Moreover, one key difference between our analysis and the one conducted by Goldin (2022b) is that we specifically examine a group initially out of the labor force. Consequently, our findings represent a particularly vulnerable demographic. This focus limits the extent to which our results can be extrapolated to the general population. Although our results are not representative for the entire US population, they reveal a critical insight: targeted examinations are crucial for policy evaluation, especially in the context of significant national policy changes such as those imposed during the COVID-19 pandemic. Our findings highlight the risk of overlooking key issues by relying on aggregated data and underscore the importance of recognizing the varied implications of policy on different sociodemographic groups and its long-term consequences. Therefore, we emphasize the importance of continuing our research strategy, focusing on how the new normal post-pandemic will shape the labor market patterns for various segments of the prime-working-age population in the future.

However, to move beyond speculative conclusions about the intensification of gender norms, additional research could utilize a survey-based questionnaire design to track the career trajectories of both women and men in couple households, linking their responses to religion or other normative factors. Additionally, to evaluate the effects of pandemic restrictions, future research could employ a staggered DDD methodology. This approach would capture the variation in specific lockdown measures, such as school closures, across US states and their impact on mothers' career and salary growth. By leveraging the increased childcare responsibilities faced by mothers during the pandemic, similar to our study, this method could use a different econometric approach to capture the causal impact of childcare on mothers' labor market developments.

When the Canadian economist Armine Yalnizyan spoke about the pandemic, she remarked: "There is no recovery without a she-covery" (Yalnizyan 2020). Although the findings of this thesis support a short-term increase in labor force participation for women relative to men, this increase can primarily be explained by the lifting of stringent mitigation measures, rather than signaling the beginning of a long-term trend for women to catch up to men's labor force participation. Previous studies show that the child penalty is a crucial factor in pre-existing gender inequalities in the US labor market. Therefore, it is alarming that the government could simply shut down nurseries and other facilities, relying on the assumption that *someone* would give up their job to care for the children without providing alternative solutions. This issue demands greater attention and must not be overlooked in future policy planning.

Bibliography

Adams-Prassl, Abi, Teodora Boneva, Marta Golin and Christopher Rauh (2022). 'Work that can be done from home: evidence on variation within and across occupations and industries'. In: *Labour Economics* 74, p. 102083. DOI: 10.1016/j.labeco.2021.102083. URL: https://doi.org/10.1016/j.labeco.2021.102083.

Anderson, Kristin J. (2015). *Modern misogyny : anti-feminism in a post-feminist era*. eng. Oxford University Press. ISBN: 9780199328178.

Arntz, Melanie, Sarra Ben Yahmed and Francesco Berlingieri (2022). 'Working from home, hours worked, and wages: Heterogeneity by gender and parenthood'. In: *Labour Economics* 76, p. 102169. DOI: 10.1016/j.labeco.2022.102169. URL: https://www.sciencedirect.com/science/article/pii/S0927537122000604.

Bhattacharya, Tithi and Lise Vogel (2017). *Social Reproduction Theory: Remapping Class, Recentering Oppression*. Pluto Press. ISBN: 9780745399881.

Bredemeier, Christian, Falko Juessen and Roland Winkler (2023). 'Bringing Back the Jobs Lost to Covid-19: The Role of Fiscal Policy'. In: *Journal of Money, Credit and Banking* 55.7, pp. 1704–1717. DOI: 10.1111/jmcb.13005. URL: https://doi.org/10.1111/jmcb.13005.

Cameron, A. Colin and Pravin K. Trivedi (2006). *Microeconometrics: Methods and Applications*. 1st ed. Cambridge: Cambridge University Press.

Carlson, Daniel L., Richard J. Petts and Joanna R. Pepin (2021). 'Flexplace Work and Partnered Fathers' Time in Housework and Childcare'. In: *Men and Masculinities* 24.4, pp. 547–570. DOI: 10.1177/1097184X211014929. URL: https://journals.sagepub.com/doi/10.1177/1097184X211014929.

CDC (2023a). *Archived Quarantine Orders*. Centers for Disease Control and Prevention. URL: https://www.cdc.gov/quarantine/archived-orders.html (visited on 05/03/2023).

CDC (2023b). *COVID-19 Pandemic Timeline*. Centers for Disease Control and Prevention. URL: https://www.cdc.gov/museum/timeline/covid19.html (visited on 25/11/2023).

Correll, Shelley J., Stephen Benard and In Paik (2007). 'Getting a Job: Is There a Motherhood Penalty?' In: *American Journal of Sociology* 112.5, pp. 1297–1338.

Cortés, Patricia and Jessica Pan (2023). 'Children and the Remaining Gender Gaps in the Labor Market'. eng. In: *Journal of economic literature* 61.4, pp. 1359–1409. ISSN: 0022-0515.

Farré, Lídia, Yarine Fawaz, Libertad González and Jennifer Graves (2022). 'Gender Inequality in Paid and Unpaid Work During COVID-19 Times'. In: *Review of*

Income and Wealth 68.2, pp. 323–350. DOI: 10.1111/roiw.12563. URL: https://onlinelibrary.wiley.com/doi/10.1111/roiw.12563.
Flood, Sarah, Miriam King, Renae Rodgers, Steven Ruggles, J. Robert Warren, Daniel Backman, Annie Chen, Grace Cooper, Stephanie Richards, Megan Schouweiler and Michael Westberry (2023). *IPUMS CPS: Version 11.0 [dataset]*. Available online at https://cps.ipums.org/cps/. Minneapolis, MN. DOI: 10.18128/D030.V11.0.
Goldin, Claudia (Apr. 2022a). *Understanding the Economic Impact of COVID-19 on Women*. NBER Working Papers 29974. National Bureau of Economic Research, Inc. URL: https://ideas.repec.org/p/nbr/nberwo/29974.html.
Goldin, Claudia (2022b). 'Understanding the Economic Impact of COVID-19 on Women'. In: *Brookings Papers on Economic Activity* 2022.1. Harvard University, pp. 1–50. URL: https://www.brookings.edu/bpea-articles/understanding-the-economic-impact-of-covid-19-on-women/.
Goldin, Claudia and Joshua Mitchell (2017). 'The New Life Cycle of Women's Employment: Disappearing Humps, Sagging Middles, Expanding Tops'. In: *Journal of Economic Perspectives* 31.1, pp. 161–182. DOI: 10.1257/jep.31.1.161. URL: https://doi.org/10.1257/jep.31.1.161.
Goodman-Bacon, Andrew and Jan Marcus (2020). 'Using Difference-in-Differences to Identify Causal Effects of COVID-19 Policies'. In: *Survey Research Methods* 14.2, pp. 153–158. DOI: 10.18148/srm/2020.v14i2.7723. URL: https://doi.org/10.18148/srm/2020.v14i2.7723.
Hauzel, Ruth and Tanuja Pattnaik (2023). 'Gender Equality in the Workplace Post-COVID-19'. In: *Global Journal of Sociology: Current Issues* 13.2, pp. 41–49. DOI: 10.18844/gjs.v13i2.9183. URL: https://doi.org/10.18844/gjs.v13i2.9183.
Heintz, James, Silke Staab and Laura Turquet (2021). 'Don't Let Another Crisis Go to Waste: The COVID-19 Pandemic and the Imperative for a Paradigm Shift'. In: *Feminist Economics* 27.1-2, pp. 470–485. DOI: 10.1080/13545701.2020.1867762. URL: https://doi.org/10.1080/13545701.2020.1867762.
Himmelweit, Susan (2017). 'Changing Norms of Social Reproduction in an Age of Austerity'. In: URL: https://api.semanticscholar.org/CorpusID:157345607.
Holder, Michelle, Janelle Jones and Thomas Masterson (2021). 'The Early Impact of Covid-19 on Job Losses among Black Women in the United States'. In: *Feminist Economics* 27.1-2, pp. 103–116. DOI: 10.1080/13545701.2020.1849766. URL: https://doi.org/10.1080/13545701.2020.1849766.
Kabeer, Naila, Shahra Razavi and Yana van der Meulen Rodgers (2021). 'Feminist Economic Perspectives on the COVID-19 Pandemic'. In: *Feminist Economics* 27.1-2, pp. 1–29. DOI: 10.1080/13545701.2021.1876906. URL: https://doi.org/10.1080/13545701.2021.1876906.
Kevane, Michael, Aishwarya Lakshmi Ratan and Diva Dhar (2024). 'Women-Led Small- and Medium-Sized Enterprises During COVID-19: Examining Barriers and Opportunities'. In: *Feminist Economics* 30.1, pp. 244–277. DOI: 10.1080/

13545701.2023.2283477. URL: https://doi.org/10.1080/13545701.2023.2283477.

Kim, Andrew Taeho, Matt Erickson, Yurong Zhang and ChangHwan Kim (2022). 'Who is the 'She' in the Pandemic 'She-Cession'? Variation in COVID-19 Labor Market Outcomes by Gender and Family Status'. In: *Population Research and Policy Review* 41, pp. 1325–1358. DOI: 10.1007/s11113-021-09693-0. URL: https://doi.org/10.1007/s11113-021-09693-0.

Kleven, Henrik, Camille Landais and Jakob Egholt Søgaard (2019). 'Children and Gender Inequality: Evidence from Denmark'. In: *American Economic Journal: Applied Economics* 11.4, pp. 181–209. DOI: 10.1257/app.20180010. URL: https://doi.org/10.1257/app.20180010.

Lafuente, Cristina, Raül Santaeulàlia-Llopis and Ludo Visschers (2022). 'Temping fates in Spain: hours and employment in a dual labor market during the Great Recession and COVID-19'. In: *SERIEs* 13, pp. 101–145. DOI: 10.1007/s13209-021-00257-1. URL: https://doi.org/10.1007/s13209-021-00257-1.

Laslett, Barbara and Johanna Brenner (1989). 'Gender and Social Reproduction: Historical Perspectives'. In: *Annual Review of Sociology* 15, pp. 381–404. DOI: 10.1146/annurev.so.15.080189.002121. URL: https://www.jstor.org/stable/2083231.

Madrian, Brigitte C. and Lars John Lefgren (2000). 'An approach to longitudinally matching Current Population Survey (CPS) respondents'. In: *Journal of Economic and Social Measurement* 26.1, pp. 31–62.

Mezzadri, Alessandra, Susan Newman and Sara Stevano (2022). 'Feminist Global Political Economies of Work and Social Reproduction'. In: *Review of International Political Economy* 29.6, pp. 1783–1803. DOI: 10.1080/09692290.2021.1957977. URL: https://doi.org/10.1080/09692290.2021.1957977.

Mohapatra, Sandeep (2021). 'Gender differentiated economic responses to crises in developing countries: insights for COVID-19 recovery policies'. In: *Review of Economic Household* 19, pp. 291–306. DOI: 10.1007/s11150-020-09512-z. URL: https://doi.org/10.1007/s11150-020-09512-z.

Moos, Katherine A. (2021). 'Coronavirus Fiscal Policy in the United States: Lessons from Feminist Political Economy'. In: *Feminist Economics* 27.1-2, pp. 419–435. DOI: 10.1080/13545701.2020.1870707. URL: https://www.tandfonline.com/doi/full/10.1080/13545701.2020.1870707.

Our World in Data (2023). *Coronavirus Pandemic (COVID-19) - the Data - Stringency Index*. Global Change Data Lab. URL: https://ourworldindata.org/covid-stringency-index (visited on 05/03/2023).

Peek, Lori and Alice Fothergill (2008). 'Displacement, Gender, and the Challenges of Parenting after Hurricane Katrina'. In: *NWSA Journal* 20.3, pp. 69–105.

Stevano, Sara, Alessandra Mezzadri, Lorena Lombardozzi and Hannah Bargawi (2021). 'Hidden Abodes in Plain Sight: The Social Reproduction of Households and Labor in the COVID-19 Pandemic'. In: *Feminist Economics* 27.1-2, pp. 271–287. DOI: 10.1080/13545701.2020.1854478. URL: https://doi.org/10.1080/13545701.2020.1854478.

Stock, James H. and Mark W. Watson (2015). *Introduction to Econometrics*. 3rd revised, Global edition. Harlow: Pearson Education.

U.S. Bureau of Labor Statistics (2023). *Civilian Labor Force Participation Rate*. URL: https://www.bls.gov/charts/employment-situation/civilian-labor-force-participation-rate.htm (visited on 03/05/2023).

Yalnizyan, Armine (2020). *No recovery without a she-covery*. The Atkinson Foundation. URL: https://atkinsonfoundation.ca/atkinson-fellows/posts/no-recovery-without-a-she-covery/ (visited on 02/05/2024).

Zhang, Mingxue, Yue Wang and Lingling Hou (2024). 'Gender norms and the child penalty in China'. eng. In: *Journal of economic behavior and organization* 221, pp. 277–291. ISSN: 0167-2681.

Appendix A

Data construction for Table 4.1

To track transitions in labor force participation over time, we use the extracted dataset from IPUMS and follow the instructions provided in the working paper by Goldin (2022a). We create a variable to indicate changes in an individual's status from one month to the next, where the variable equals 1 if they entered the labor force and -1 if they exited.

The construction of Group 1 is based on the following criteria:

1. Entered the labor force sometime between April 2019 and February 2020.
2. Were still in the labor force as of their last pre-pandemic *(before March 2020)* observation.
3. Had at least one observation in the pandemic period *(after March 2020)*.

The construction of Group 2 is based on the following criteria:

1. Consistently in the labor force from April 2019 to February 2020, without any identified changes in their labor force status.
2. Contains at least one observation during the pandemic period *(after March 2020)*.

Finally, for both groups, we established a variable to count the frequency of transitions in and out of the labor force during the pandemic.

Appendix B

Mean values of subsamples

The means of the independent variables from Equation 4.1 are presented in Table B.1.

Table B.1: The mean values of the independent variables in the total CPS sample versus the subsample used in the replicated regression analysis.

Independent variables	*Means of total CPS sample*	*Means of restricted sample for the replicated regression analysis*	*Means difference*
Female	0.5152	1	-0.4848***
Respondent's age			
20-24	0.0418	0.0818	-0.0400***
25-29	0.0497	0.1227	-0.0730***
30-34	0.0594	0.1463	-0.0869***
35-39	0.0638	0.1609	-0.0971***
40-44	0.0620	0.1571	-0.0951***
45-49	0.0635	0.1627	-0.0992***
>50	0.4265	0.1684	0.2581***
Youngest child's age			
0-4 years	0.0704	0.1553	-0.0849***
5-13 years	0.0902	0.2331	-0.1429***
14-17 year	0.0374	0.0911	-0.0537***
18-29	0.0538	0.0836	-0.0300***
No residential children	0.7483	0.4370	0.3113***
College graduate	0.2693	0.4688	-0.1995***
Black	0.0953	0.1006	-0.0053***
Hispanic	0.1372	0.1387	-0.0015*
Service occupation	0.0539	0.1235	-0.0700***
No spouse	0.5417	0.4197	0.1220***
Observations	3,622,308	172,103	

† P-Value below 10 %(*); 5 %(**); 1 %(***).

The means of the independent variables from Equation 4.3 are presented in Table B.2.

Table B.2: The mean values of sociodemographic variables in the total CPS sample versus the restricted subsample used in the DDD analyses.

Sociodemographics	*Means of total CPS sample*	*Means of restricted sample for the DDD analysis*	*Mean differences*
Female	0.5152	1	-0.4848***
Respondent's age			
20-24	0.0418	0.1540	-0.1122***
25-29	0.0500	0.1254	-0.0757***
30-34	0.0594	0.1475	-0.0880***
35-39	0.0638	0.1500	-0.0862***
40-44	0.0620	0.1357	-0.0738***
45-49	0.0635	0.1320	-0.0685***
>50	0.4265	0.1553	0.2712***
Youngest child's age			
0-4 years	0.0704	0.2372	-0.1668***
5-13 years	0.0902	0.2050	-0.1149***
14-17 year	0.0374	0.0634	-0.0260***
18-29	0.0540	0.0690	-0.0150***
No residential children	0.7483	0.4281	0.3201***
College graduate	0.2693	0.2627	0.0066***
Black	0.0953	0.1043	-0.0090***
Hispanic	0.1372	0.1043	0.0330***
Service occupation	0.0540	0.0380	0.0157***
No spouse	0.5417	0.4300	0.1117***
Observations	3,622,308	264,211	

† P-Value below 10 %(*); 5 %(**); 1 %(***).

Appendix C

Counterfactual

In Figure C.1 and Figure C.2, DDD analyses are presented for different sociodemographic groups, illustrating the development of labor force participation rates for the treated and counterfactual subsamples.

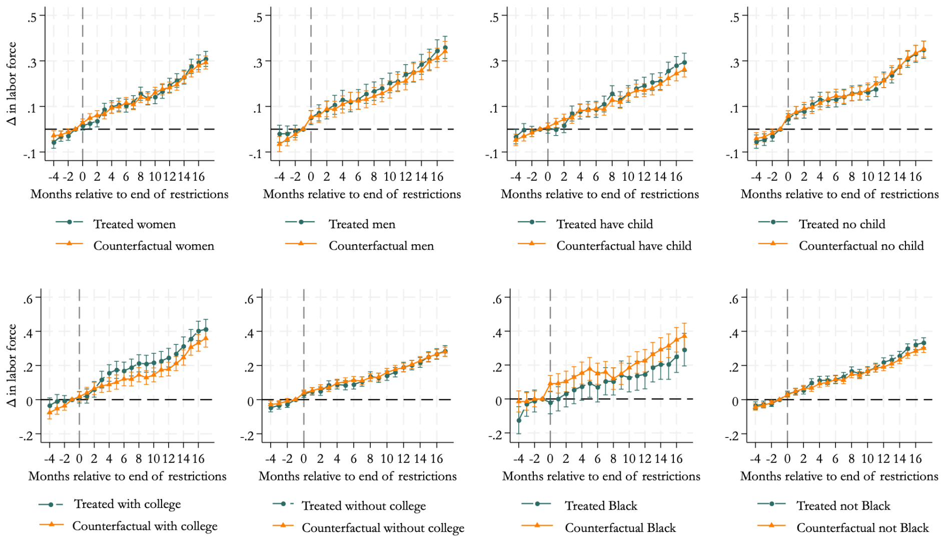

Figure C.1: DDD analyses across genders, parenthood status, college graduates and Black individuals, with treatment in June 2022 and placebo in June 2018.

†Includes individual FE and the vertical lines denote 95% confidence intervals.

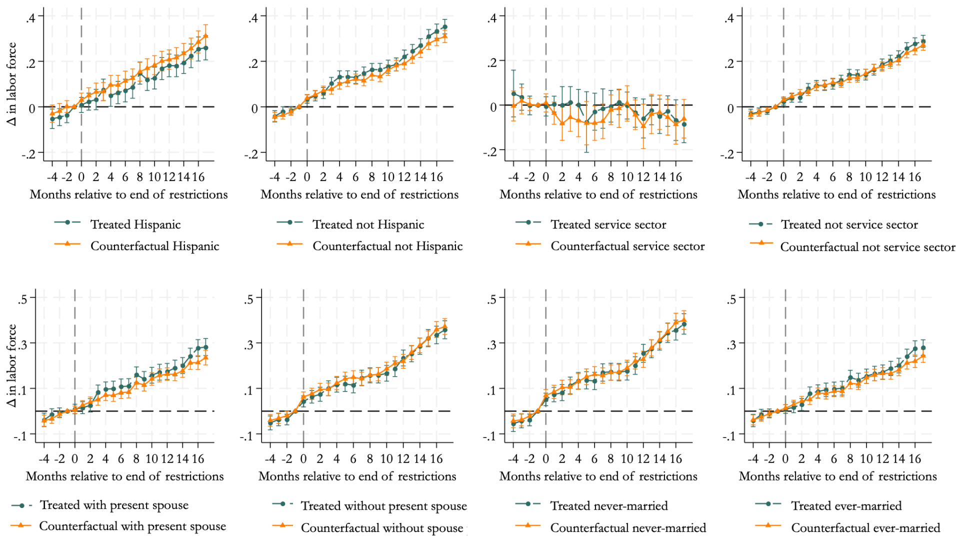

Figure C.2: DDD analyses across Hispanic individuals, service occupations and marital status, with treatment in June 2022 and placebo in June 2018.

†Includes individual FE and the vertical lines denote 95% confidence intervals.

Appendix D

Replicated regression analysis with labor force

In the following Table 5.1, the results from the replicated regression Equation 4.1 with the change in labor force participation as the dependent variable are presented.

Table D.1: Annual changes in labor force rates for women between 20 and 54 years from January 2018 to November 2021.

	Women in labor force in year t, month m			
	Main effects	*Plus child interactions*	*Plus race and occupation interactions*	*Plus marital interactions*
Respondent's age				
20-24	-0.0716^{***}	-0.0717^{***}	-0.0716^{***}	-0.0757^{***}
	(0.005)	(0.005)	(0.005)	(0.005)
25-29	-0.0138^{***}	-0.0139^{***}	-0.0138^{***}	-0.0162^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
30-34	-0.0065^{*}	-0.0065^{*}	-0.0064^{*}	-0.0085^{**}
	(0.004)	(0.004)	(0.004)	(0.004)
35-39	0.0109^{***}	0.0110^{***}	0.0111^{***}	0.0091^{***}
	(0.004)	(0.004)	(0.004)	(0.004)
40-44	0.0089^{***}	0.0090^{***}	0.0091^{***}	0.0080^{**}
	(0.003)	(0.003)	(0.003)	(0.003)
45-49	0.0058^{*}	0.0059^{*}	0.0059^{*}	0.0055^{*}
	(0.003)	(0.003)	(0.003)	(0.003)
Youngest child's age				
0-4 years	-0.0345^{***}	-0.0237^{***}	-0.0238^{***}	-0.0194^{***}
	(0.003)	(0.005)	(0.005)	(0.005)
5-13 years	-0.0102^{***}	-0.0081^{**}	-0.0079^{**}	-0.0048
	(0.003)	(0.004)	(0.004)	(0.004)
14-17 years	0.0061^{*}	0.0088^{**}	0.0091^{**}	0.0117^{***}
	(0.003)	(0.004)	(0.004)	(0.005)

Table D.1 Continued from previous page

	Women in labor force in year t, month m			
	Main effects	*Plus child interactions*	*Plus race and occupation interactions*	*Plus marital interactions*
18-29 years	0.0077^{**}	0.0111^{**}	0.0115^{**}	0.0136^{***}
	(0.004)	(0.005)	(0.005)	(0.005)
College graduate	0.0365^{***}	0.0364^{***}	0.0382^{***}	0.0393^{***}
	(0.003)	(0.003)	(0.003)	(0.003)
Black	-0.0271^{***}	-0.0270^{***}	-0.0229^{***}	-0.0256^{***}
	(0.003)	(0.003)	(0.005)	(0.005)
Hispanic	-0.0283^{***}	-0.0283^{***}	-0.0281^{***}	-0.0288^{***}
	(0.003)	(0.003)	(0.004)	(0.005)
Service occupation	0.0175^{***}	0.0175^{***}	0.0265^{***}	0.0259^{***}
	(0.003)	(0.003)	(0.004)	(0.004)
Start year 2018	−0.0028	−0.0028	−0.0029	−0.0028
	(0.006)	(0.006)	(0.006)	(0.006)
Start year 2019	−0.0040	−0.0040	−0.0040	−0.0040
	(0.004)	(0.004)	(0.004)	(0.004)
Spring	0.0007	0.0006	0.0006	0.0005
	(0.003)	(0.003)	(0.003)	(0.003)
Summer	−0.0003	−0.0003	−0.0003	−0.0005
	(0.003)	(0.003)	(0.003)	(0.003)
Fall	0.0037	0.0037	0.0037	0.0036
	(0.003)	(0.003)	(0.003)	(0.003)
Prepandemic to pandemic (pre-pan)	-0.0293^{***}	-0.0222^{***}	-0.0160^{***}	-0.0146^{**}
	(0.005)	(0.005)	(0.006)	(0.006)
Pandemic to pandemic (pan-pan)	-0.0191^{***}	-0.0181^{**}	-0.0160^{**}	−0.0138
	(0.007)	(0.007)	(0.008)	(0.008)
Pre-pan × college	0.0187^{***}	0.0191^{***}	0.0150^{***}	0.0138^{***}
	(0.004)	(0.004)	(0.005)	(0.005)
Pan-pan × college	0.0109^{**}	0.0110^{**}	0.0096^{*}	0.0078
	(0.005)	(0.005)	(0.005)	(0.005)
Pre-pan × children under age 5		-0.0234^{***}	-0.0233^{***}	-0.0180^{**}
		(0.007)	(0.007)	(0.008)
Pan-pan × children under age 5		−0.0116	−0.0115	−0.0038
		(0.008)	(0.008)	(0.009)
Pre-pan × children age 5-13		−0.0084	−0.0088	−0.0091
		(0.006)	(0.006)	(0.006)
Pan-pan × children age 5-13		0.0033	0.0033	0.0025
		(0.006)	(0.006)	(0.007)
Pre-pan × children age 14-18		-0.0136^{*}	-0.0144^{**}	-0.0151^{**}
		(0.007)	(0.007)	(0.007)

Table D.1 Continued from previous page

	Women in labor force in year t, month m			
	Main effects	*Plus child interactions*	*Plus race and occupation interactions*	*Plus marital interactions*
Pan-pan × children age 14-18		0.0087 (0.007)	0.0085 (0.007)	0.0074 (0.008)
Pre-pan × children age 18-30		−0.0050 (0.007)	−0.0054 (0.007)	−0.0062 (0.008)
Pan-pan × children age 18-30		−0.0069 (0.009)	−0.0071 (0.009)	−0.0080 (0.009)
Pre-pan × Black			−0.0094 (0.008)	−0.0080 (0.008)
Pan-pan × Black			−0.0033 (0.009)	−0.0012 (0.009)
Pre-pan × Hispanic			0.0003 (0.007)	0.0008 (0.007)
Pan-pan × Hispanic			−0.0014 (0.008)	−0.0006 (0.008)
Pre-pan × service occupation			−0.0229*** (0.006)	−0.0225*** (0.006)
Pan-pan × service occupation			−0.0059 (0.007)	−0.0051 (0.007)
No spouse				0.0113*** (0.003)
Pre-pan × no spouse				−0.0017 (0.005)
Pan-pan × no spouse				−0.0028 (0.006)
Pre-pan × no spouse × children under age 5				−0.0232* (0.014)
Pan-pan × no spouse × children under age 5				−0.0375** (0.017)
Constant	0.9362*** (0.006)	0.9334*** (0.006)	0.9307*** (0.006)	0.9256*** (0.006)
R2	0.0231	0.0234	0.0236	0.0239
Adjusted R2	0.0230	0.0232	0.0234	0.0237
Observations	187,588	187,588	187,588	187,588

† P-Value below 10 %(*); 5 %(**); 1 %(***) and standard errors in brackets.

Appendix E

DDD analyses

In Figure E.1, the results from Equation 4.3 are presented, categorizing new groups of women by marital status, motherhood and educational attainment.[16]

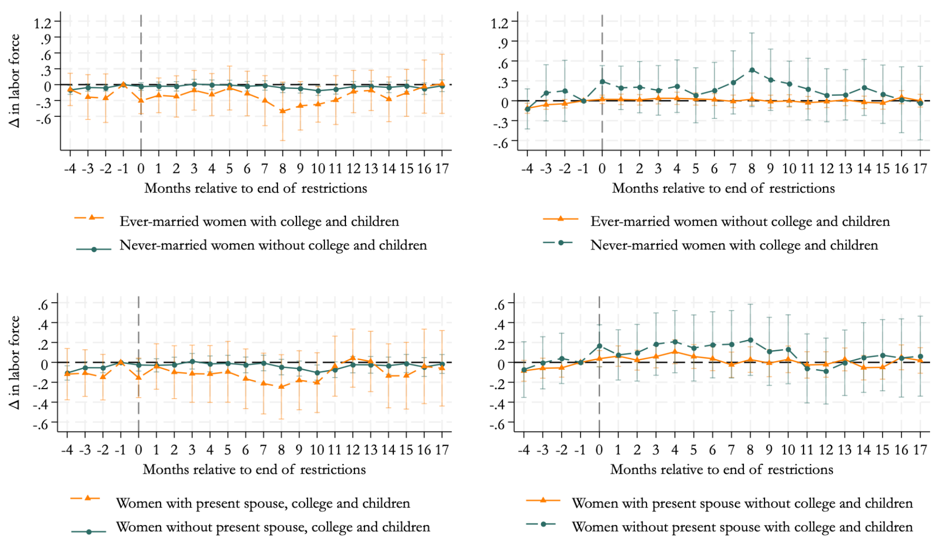

Figure E.1: DDD analyses of labor force participation entry rates, with June 2022 as the treatment indicator, interacted with marital status, education level and residential children. The analyses control for seasonal variations and individual-specific effects.

†The vertical lines denote 95% confidence intervals. Ever-married women includes those who are currently married, regardless of whether their spouses are present or not, separated, divorced or widowed. Women without present spouses includes those who are currently married with absent spouses, separated, divorced or widowed.

[16]The groups are G_{11}: ever-married women with college and children (never-married women without college and children), G_{12}: ever-married women without college and children (never-married women with college and children), G_{13}: women with present spouse, college and children (women without present spouse, college and children) and G_{14}: women with present spouse without college and children (women without present spouse with college and children).