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COVID-19 She-Cession: The Employment Penalty of Taking Care of Young Children

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Abstract

The COVID-19 outbreak and the measures to contain the virus have caused severe disruptions to labor supply and demand worldwide. Understanding who is bearing the burden of the crisis and what drives it is crucial for designing policies going forward. Using the U.S. monthly Current Population Survey data, this paper analyzes differences in employment responses between men and women. The main finding is that less educated women with young children were the most adversely affected during the first nine months of the crisis.The loss of employment of women with young children due to the burden of additional childcare is estimated to account for 45 percent of the increase in the employment gender gap, and to reduce total output by 0.36 percent between April and November 2020.

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I. INTRODUCTION

The COVID-19 pandemic triggered an unprecedented economic crisis that required unique actions to contain the spread of the virus. Due to the infectious nature of the virus, governments had to impose lockdowns restricting economic activity and closing schools to contain its spread. Economic sectors requiring face-to-face interactions to operate, called social sectors, were hit the hardest, and so were their workers.

Women have been particularly impacted by the crisis for many reasons. Women's employment is highly concentrated in social sectors.[2] For example, in the United States, 66 percent of total female workers were employed in social sectors as of January 2020. Women are also traditionally more likely to be in charge of housework and taking care of children. In the United States, before the crisis, women spent 60 percent more time doing unpaid work than men (Alonso and others., 2019). Lockdowns and school closures have dramatically increased housework, especially for families with young children.

This paper investigates the impact of the pandemic on employment across industries, occupations, education levels, and family structures, during the first nine months of the crisis (from April to December). Using U.S. monthly Current Population Survey (CPS) data, we identify less educated women with children under 12 years old as the hardest-hit workers. To confirm this descriptive statistic, we perform an empirical investigation using a linear probability model of the individual likelihood of employment that controls for differences in sectoral employment, occupation, age, race, marital status, education, and geography.

We find that being a woman with at least one child under 12 years old reduced the probability of being employed by 3 percentage points on average compared to a man with similar characteristics during the first nine months of crisis. In contrast, we find that being a woman without a child under 12 years old reduced the probability of being employed by 1 percentage point, compared to a man with similar characteristics (less than half of the impact on women with a child under 12 years old). This result suggests that the risk of infection and intervention measures such as school closures that increased the childcare at home are key drivers in the employment gender gap observed during the COVID-19 crisis. Further, we perform a decomposition exercise and find that the extra impact on women with young children explains 45 percent of the total employment gender gap between April and December. This is a large share since employed women living with children under 12 account for only 25 percent of women's total employment before the crisis. We also find that race and level of education play an important role, as African American women with young children and less educated women with young children are among the most affected by the crisis.

Finally, to quantify the overall economic cost associated with the extra-childcare burden on female employment induced by the pandemic and measures to contain it, we use a

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[2]Social sectors are defined as in Shibata (2020). Industries are considered as social if their output requires interpersonal interaction to consume, for example air transportation, veterinary services, and hospitality and tourism.

production model calibrated to the United States. In this model, aggregate labor input is a CES combination of men's and women's total hours worked, assuming an incomplete substitutability between men and women. Estimating a counterfactual employment series for women with young children that cancels the extra burden (in employment terms) on this group of women, we find that the effect of the additional childcare on the employment of women with young children reduced total U.S. output by 0.36 percent between April and November 2020. This estimate is a lower bound, since it abstracts from other possible short-term output losses, for example, from school closures such as those related to school employees or suppliers to schools.

Our findings contribute to the growing literature on the employment effects of the COVID-19 crisis that has focused on the beginning of the pandemic (Adams-Prassl and others, 2020; Alon and others, 2020; Montenovo and others, 2020); and Shibata, 2020). Our main contribution relative to this literature is that we identify women with young children as being impacted harder by the crisis using data for the entire year of 2020. Our work suggests that the extra childcare needs played an essential role in explaining the increased in the gender employment gap since the onset of the pandemic, supporting some early conjectures about the impact of the crisis on gender inequality (Dingel and others. 2020; Fabrizio and others, 2020; Georgieva and others, 2020; and Gates 2020). Our paper also contributed to literature that quantifies the impact of the employment gender gap on the economic recovery (Alon and others, 2020).

The rest of the paper is organized as follows. Section II provides a brief literature review about the impact of COVID-19 on female employment and its drivers. Section III.A provides an overview of developments in employment by gender in the U.S. since the onset of the crisis. Section III.B zooms on differences on education, sectors, and occupations. Section III.C presents the formal empirical analysis. Section IV estimates the economic costs of extra childcare and other unidentified factors that increased the gender employment gap during the crisis. Section V concludes.

II. COVID-19 AND FEMALE EMPLOYMENT: RELATED RESEARCH

Unlike previous recessions, the COVID-19 crisis employment losses have been larger for women than for men. In the literature, two main drivers have been identified that would explain why we are facing a she-cession:[3] (i) lockdown measures and fear of contagion have mostly affected sectors/occupations with a high concentration of female workers; and (ii) the closures of schools and daycare centers, and the implementation of remotely learning have increased childcare needs forcing many parents, particularly mothers, to choose between keeping their jobs or taking care of children.

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[3]She-cession is a colloquial term that indicates that the crisis impacted women's employment more than men. The term is used in opposition to the use of mancession expression during the 2008 global financial crisis.

The COVID-19 pandemic has affected industries and jobs that require direct contact, and women's employment is concentrated in these sectors. An extensive literature has shown that women's occupational and sectoral employment has contributed to increased unemployment relative to men. Adams-Prassl and others. (2020), using real-time survey evidence from the United Kingdom, the United States, and Germany in March and April 2020, find that workers who have non-teleworkable occupations are more likely to have lost their jobs; however, they find that occupation fixed effects and the percentage of task one can do from home cannot explain the total increase in the employment gender gap. Shibata (2020) and Montenovo and others. (2020), using CPS from the first months of the pandemic find that in the United States, women were more affected than men during the pandemic and part of this difference is attributable to sectors and occupations employment. Alon and others (2020) using early data from pandemic argue that women employment loss is caused by sectoral employment and childcare needs.

Women are also traditionally the primary caregiver. As documented by Alon and others (2020), before the crisis, among married parents in the United States who both work full time—represent 44 percent of married couples with children—women provided about 60 percent of childcare: men perform 7.2 hours of childcare per week versus 10.3 hours for women. When the needs of childcare increase (like during this crisis), women are more likely than men to give up their job to take care of children. Zamarro and Prados (2020), for example, find that, in the United States, women have carried a heavier load than men in the provision of childcare during the COVID-19 crisis, even while still working. Hupkau and Petrangolo (2020) find that in United Kingdom., mothers took on a larger share of increased childcare needs, even though fathers became the primary childcare providers in an important share of households. Russel and Sun (2020), using state-level variations in the United States, show that childcare center closures or imposed class size restrictions increased the unemployment of mothers of small children. Using novel mobility indicators for Italy, Portugal, and Spain at the provincial level, Caselli and others (2020a) provide further evidence that school closures and other lockdown measures have also impacted women more than men. Furthermore, using data for 128 countries, Caselli and others (2020b) show that lockdown measures tend to have statistically significant negative effect of mobility in particular for women, less educated and minorities. Beyond childcare, women are also more likely than men to provide care to others in need, including elderly and disable (American Psychological Association, 2011).

Beyond these main factors, there is also some evidence that fear of the virus is higher among women, in particular women in jobs where they would have to take additional risks in Italy (Benassi and others, 2020) and in the United States that women are more likely to perceive their working environment as riskier than men (Covington and Kent, 2020).

III. What do the Data tell Us? An Empirical Analysis

We use monthly U.S. microdata from the Current Population Survey (CPS) between January and December 2020 collected from the IPUMS-CPS database (Flood and others, 2020). The CPS is jointly sponsored by the U.S. Census Bureau and the U.S. Bureau of Labor

Statistics (BLS) and is the primary source of labor force statistics for the population of the United States. Nationwide, comprehensive interviews of approximately 60,000 households (covering about 150,000 individuals) collect information about workers' labor force and employment status, industry, occupation, demographics, and family structure.[4] This rich dataset allows us to investigate the short-term gendered effects of the pandemic across a variety of worker types.

A. Labor Market During the Pandemic: A Gender Perspective

We begin by documenting developments in total hours worked by gender since the onset of the crisis. For each month, we select all individuals assigned as employed with positive hours worked.

Figure 1 shows that total hours worked plummeted more for women than for men in April 2020 and have partially recovered afterward at a slower pace for women than for men. Furthermore, decomposing total hours worked in average hours worked and employment, Figure 1 shows that the reduction in total hours worked reflected mostly a loss of jobs rather than a reduction of hours per worker, a regularity observed in past recessions. However, a distinguished aspect of the pandemic recession is that employment losses for women have been larger than for men.

Figure 1. Transition of Total Hours Worked by Gender, January-December 2020

Sources: Current Population Survey (CPS); authors' calculations.
Note: January 2020 is the reference point. The total hours series is plotted as the logarithm of total hours worked in the current month divided by the total hours worked in January. Formally, let H_t be the total hours worked in month t, and assume that $t = 0$ represents January. Then, the plotted total hours series is given by $\log(H_t/H_0)$. Note that this series can be decomposed into the contributions of employment and average hours worked. Let E_t and h_t be the employment level and average hours worked, respectively, in month t. Since, by definition, $H_t = h_t E_t$ for all t, then $\log(H_t) = \log(h_t) + \log(E_t)$ for all t. This equality also holds in January, so $\log(H_0) = \log(h_0) + \log(E_0)$. By subtracting one equality from the other, we get $\log(H_t/H_0) = \log(h_t/h_0) + \log(E_t/E_0)$. The bars in the figures represent the two terms on the right-hand side of the last equality.

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[4]The CPS does not publish earnings data monthly.

Figure 2 shows the gender gap in total hours worked decomposed by average hours worked and employment. The larger gender gap in total hours worked also reflects mostly a greater loss of jobs for women for most of the period.

Figure 2. Decomposition of the Gender Gap in Total Hours Worked, January-December 2020

Sources: Current Population Survey (CPS); authors' calculations.

Note: As in Figure 1, the employment and average hours series are plotted as the ratio between the current month value and the value in January. Formally, for each gender, we are plotting E_t/E_0 in the middle figure and h_t/h_0 in the right-most figure. For the total hours gender gap decomposition, first define $G_{H,t} \equiv H_{f,t}/H_{m,t}$ as the gender gap in total hours, $G_{E,t} \equiv E_{f,t}/E_{m,t}$ as the gender gap in employment, and $G_{h,t} \equiv h_{f,t}/h_{m,t}$ as the gender gap in average hours. Then, from the definition of the gaps, we have that $G_{H,t} = G_{h,t} \times G_{E,t}$ for all t. By taking the logarithm of the previous equality, this gives $\log(G_{H,t}) = \log(G_{h,t}) + \log(G_{E,t})$ for all t. In particular, this equality also holds in January, so we have that $\log(G_{H,0}) = \log(G_{h,0}) + \log(G_{E,0})$. By subtracting one equality from the other, we have $\log(G_{H,t}/G_{H,0}) = \log(G_{h,t}/G_{h,0}) + \log(G_{E,t}/G_{E,0})$. The three elements of the last equality are plotted in the left hand-side chart.

This change in employment reflects both an increase in unemployment and a decline in labor force participation. Total unemployment rose sharply in April. The rise in unemployment was larger among women than men, generating an increase in the unemployment gender gap. The unemployment gender gap picked in April and declined afterward, almost closing in December. Male and female labor force participation declined sharply in April recovering gradually between April and July and declining again afterwards. In contrast to trends in employment, trends in male and female labor force participation were similar, leading to larger increase in women out of labor force since female labor force participation was lower than men in January.

B. What Drives the Widened Gender Employment Gaps during the Crisis

In this section, we zoom in on workers' characteristics to gather further information on who lost jobs, and why, during the crisis. We group workers according to their education level (college or no college degree), race (white or African-American), industry (262 in total), occupation (525 in total) and family features (parents with or without young children). For the industry and occupation labels, we use the classifications of social industries and teleworkable occupations as in Shibata (2020).[5] Industries are considered social if their output requires

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[5]Shibata (2020) adapted to the CPS the social industry classification proposed by Kaplan and others (2020) and the teleworkable classification proposed by Dingel and Neiman (2020) and Mongey and others. (2020). We thank the author for

(continued…)

interpersonal interaction to consume. Occupations are labeled as teleworkable if workers are able to work remotely. Finally, within each group, we categorize workers according to the presence or absence of young children in the household (at least one child younger than 12 years old).

We compare women and men's employment trajectories within each group of workers using January 2020 as the reference point.[6] We start by looking at the contribution to overall employment losses of women and men that came from individuals with and without young children (Figure 3). For both women and men, the largest share of the employment change is explained by individuals without young children, as they represent a larger share of the population. However, in every month since the onset of the crisis, the share of job losses explained by individuals with young children is higher among women than men. From April to December, this figure averages to 32 percent for women, while 24 percent for men.

Figure 3. Employment Change Decomposition, January-December 2020

Sources: Current Population Survey (CPS); authors' calculations.
Note: The total employment series are plotted as the percent change from January to the current month. Formally, for each gender, we are plotting $\%\Delta E_t = (E_t - E_0)/E_0$ as the black dashed line. Let $E_{k,t}$ be the employment level of individuals with young children status k in month t, where $k = 0$ refers to those without young children and $k = 1$ to those with young children. Note that $E_t = E_{k=0,t} + E_{k=1,t}$ for every month t. Similarly, define $\%\Delta E_{k,t} = (E_{k,t} - E_{k,0})/E_{k,0}$ as the percent change for individuals with children status k. Also, let $W_k = E_{k,0}/E_0$ be the employment weight in January of those with children status k. Then, we can decompose the total employment change series as $\%\Delta E_t = W_{k=0} \times \%\Delta E_{k=0,t} + W_{k=1} \times \%\Delta E_{k=1,t}$. The darker bars represent the first term on the right-hand side of the decomposition, and the lighter bars represent the second term.

Focusing on the level of education, Figure 4 shows that women and men without college education have experienced a large decline in employment during the crisis compared with educated workers. This is particularly the case for women with young children, which have

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kindly providing the data containing the CPS codes for industries and occupations already labeled as social and teleworkable, respectively.

[6]See Note in Figure 2 for a description of how the series were constructed.

largely contributed to increase the employment gender gap. The employment gender gap among men and women without a college education and with young children is more than three times the employment gender gap experienced by men and women with a college education independently of children, and men and women without a college education and without children. Considering the high correlation between education and income levels, evidence suggests that the crisis is not only increasing the employment gender gap but is also exacerbating income inequality.

Figure 4. Employment Developments by Education Level, January-December 2020
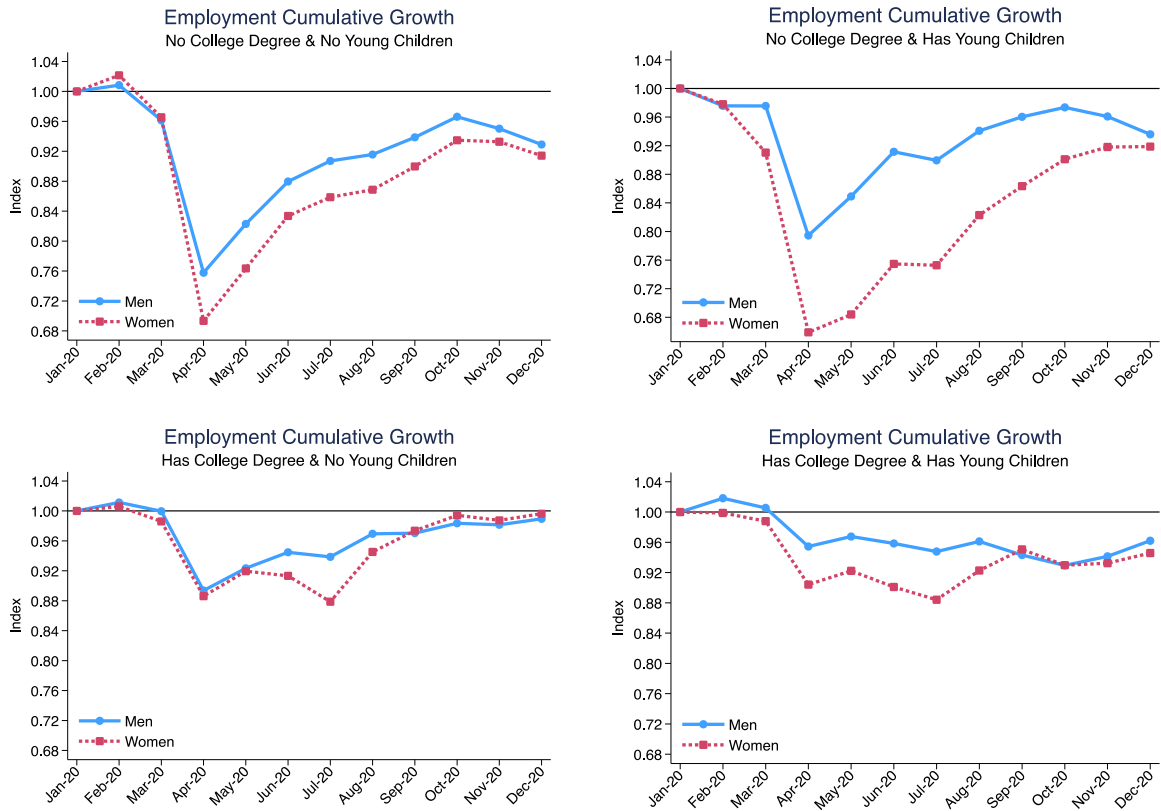
Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020.

We also look at the pattern of employment focusing on differences between race, in particular white and African-American men and women with young children. Figure 5 shows that African-American women were the most affected compared to all others.

Figure 5. Employment Fluctuations by Race, January-December 2020

Employment Cumulative Growth
White & Has Young Children

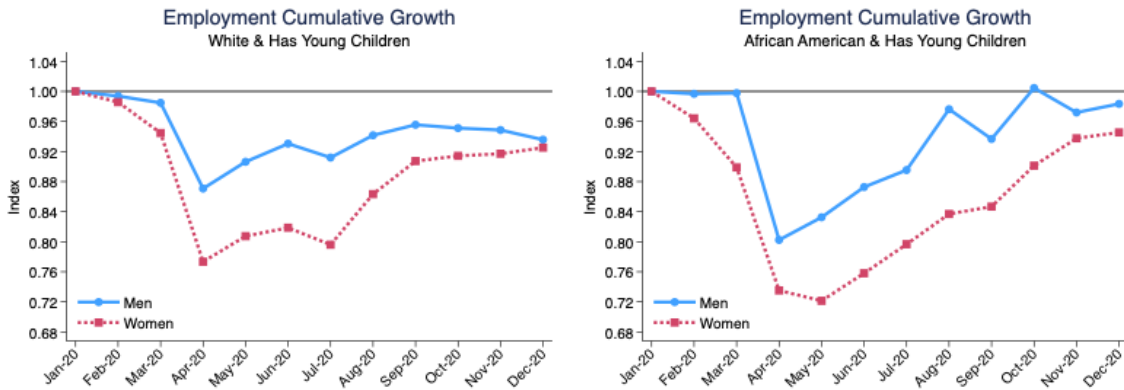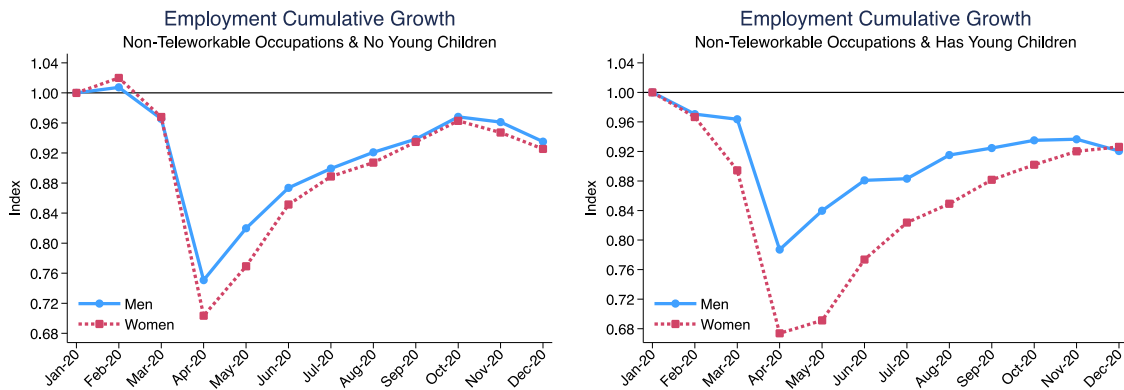Employment Cumulative Growth
African American & Has Young Children

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020. In the appendix we present similar charts for white and African American workers without young children.

We now focus on the groups most likely to suffer large employment losses during the crisis, namely workers who hold non-teleworkable occupations or are involved in social sectors. A similar pattern is observed among workers unable to work from home (Figure 6). Employment disparities by gender are quite different between those with and without young children. In particular, mothers of young children with jobs requiring in-person interactions have experienced a much slower employment recovery compared with women without young children and to fathers of young children holding similar jobs.

Figure 6. Employment Fluctuations in Non-Teleworkable Occupations, January-December 2020

Employment Cumulative Growth
Non-Teleworkable Occupations & No Young Children

Employment Cumulative Growth
Non-Teleworkable Occupations & Has Young Children

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020. In the appendix we present similar charts for teleworkable occupations.

Lastly, we analyze employment development in social industries (Figure 7). Interestingly, among workers without young children, men and women involved in the same industries have experienced similar job losses, suggesting that the type of industry has been a key driver of the evolution of employment among workers without children. This has not been the case for female workers with young children, who have experienced a protracted loss of employment over several months since April compared to all other workers in similar industries.

Figure 7. Employment Fluctuations in Social Industries, January-December 2020

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020. In the appendix we present similar charts for non-social industries.

In summary, data analysis shows that women with young children have been disproportionately affected compared with other women and men in terms of employment losses, though also women without children have witnessed to a certain extent a larger loss in employment than men with similar characteristics. This points to additional childcare that women had to provide as an important driver of the increased employment gender gap. Notably, among women with young children, the less educated have experienced the largest loss of employment, suggesting that the pandemic and related lockdown measures such as school closures are not only increasing the gender employment gap but also income inequality.

C. Measuring Women's Employment Penalty: A Regression Approach

The evidence so far points to a significant employment penalty for women throughout the pandemic, especially for the mothers of young children. In this section, we corroborate these results with empirical evidence. Our approach is to run monthly linear probability models (LPM) of the employment probability on a female dummy and a set of controls.[7] Furthermore, to fully capture differentiated effects coming from the presence of young children, we run the regressions separately for those with and without young children in the household. The set of

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[7]As regressions are estimated for each month separately, our results are being controlled for any seasonal variations that may have occurred during the period or that occur regularly.

controls contains six age groups, three racial categories, six education groups, a married dummy, 17 industry groups, 12 occupation groups, a social industry dummy, a teleworkable occupation dummy, and a dummy for each state. Since regressions are performed separately for those with and without young children, the estimates of the female dummy and controls are allowed to vary between these two groups.[8]

To estimate the regression models, we considered the sample of individuals assigned by the CPS as employed, unemployed, and out of the labor force but not retired. Note that the CPS records information about industry and occupation only for the employed and unemployed, but not for those out of the labor force. To get around this and keep those out of the labor force in the sample, we created a specific industry/occupation classification for that group.

To formalize our regression specification, we index individuals by i, months by t, and the young children status by k. Let $E_{i,t,k}$ be the employment indicator, $F_{i,t,k}$ the female indicator, and $\mathbf{X}_{i,t,k}$ the vector of controls. Then, our regression equation can be stated as

$$\Pr\big(E_{i,t,k} = 1 \mid F_{i,t,k}, \mathbf{X}_{i,t,k}\big) = \alpha_{t,k} + \beta_{t,k} F_{i,t,k} + \boldsymbol{\gamma}'_{t,k} \mathbf{X}_{i,t,k} + \varepsilon_{i,t,k}, \tag{1}$$

where $\varepsilon_{i,t,k}$ is the error term. We start by inspecting the estimates of the $\beta_{t,k}$ coefficients, which can be interpreted as the average marginal effects (AME) of being a female on the likelihood of employment. First, we want to look at the sign of the estimates. Negative values would confirm the women's employment penalty. Second, we want to compare how the estimates change over the months. More negative values since April would suggest higher penalties for women since the onset of the pandemic. Third and finally, we want to compare the sizes of the coefficients across the children or no children statuses. More negative values for the young children estimates would indicate that the required additional care for children by mothers could be a key factor for widening gender differences.

The estimates confirm findings in the previous section (Figure 8). Before the systematic lockdowns, the estimates for those without young children have no statistical significance, indicating no significant employment penalty for women. Women with young children, on the other hand, already faced a certain degree of employment penalty before the pandemic. However, with the advent of lockdowns, all the estimates become highly significant and negative, corroborating the story that severe employment penalties on women were triggered during the recession. Furthermore, there are considerable differences in the sizes of the estimated coefficients across the two children status. The estimated coefficients for the sample with young children are more negative than the ones for the sample without young children.

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[8]Due to the lack of data availability, the analysis does not account for the potential impact of the UI benefits that workers with children younger than 17 received during the crisis, which could have created incentives for those individuals to delay searching for a job.

This evidences that having young children at home indeed contributed to the aggravation of employment gender disparities.

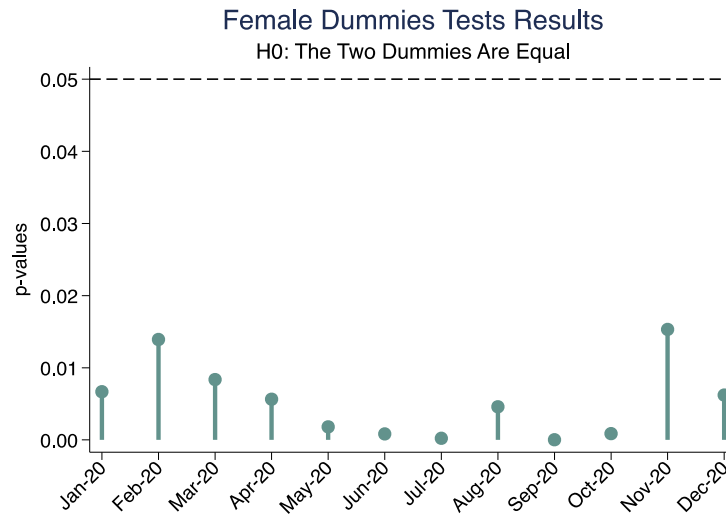**Figure 8. Regression Estimates for the Female Dummy Variable**
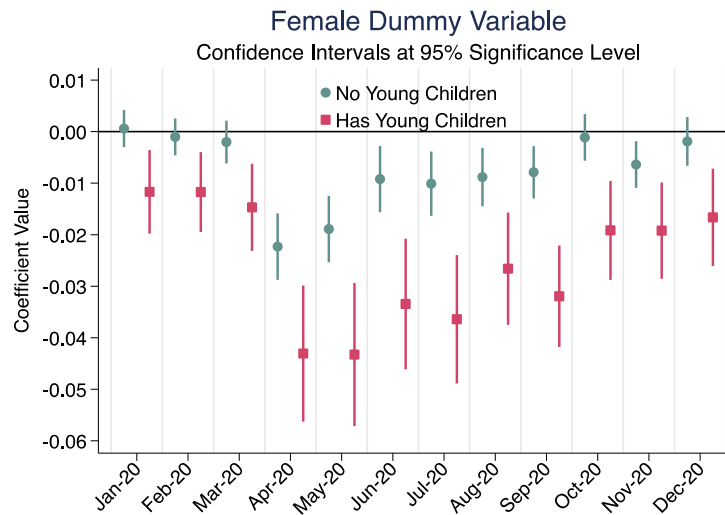
Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the estimates for the female dummy variables calculated from the logistic regressions described by equation (1). The points represent the estimated coefficients and the lines represent the confidence intervals at a significance level of 95 percent.

To provide further evidence on the different impacts of the crisis on women with and without young children, we test for the equality of the two female dummy coefficients each month separately.[9] We perform cross-model hypothesis tests using a seemingly unrelated estimation approach for a Wald test (Weesie, 1999). For each month, the null hypothesis is that the two female dummies are equal. The monthly p-values for the tests are presented in Figure 9. From January to December, all p-values are smaller than 5 percent, indicating that we can reject the equality of the dummies at the 5 percent level.

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[9]The fact that some confidence intervals reported in Figure 8 overlap does not necessarily imply that the two female dummies are not statistically different from each other; see Schenker and Gentleman (2001).

Figure 9. Testing the Equality of the Two Female Dummies

Female Dummies Tests Results
H0: The Two Dummies Are Equal

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the p-values of the hypothesis tests in which we test for the equality of the two female dummy coefficients. The null hypothesis is that the two coefficients are equal. The tests are performed separately for each monthly regression.

The resulting figures quantify that, with the onset of the crisis, the female effect on the likelihood of employment has deteriorated in general, but much more for those with young children. We next take a closer look at the size of these differences before and after the pandemic (Figure 10). The numbers displayed between the two curves represent the differences in female AMEs between those with and without young children. Before the crisis, these differences were all less than or equal to 1.3 percentage points. However, after the start of the recession, although all AMEs became quite negative, the ones for those with young children decreased much more. The differences in all subsequent months are considerably higher than 1.3 percentage points (except for November), reaching more than 2 percentage points in five months.

Figure 10. Comparison of Average Marginal Effects
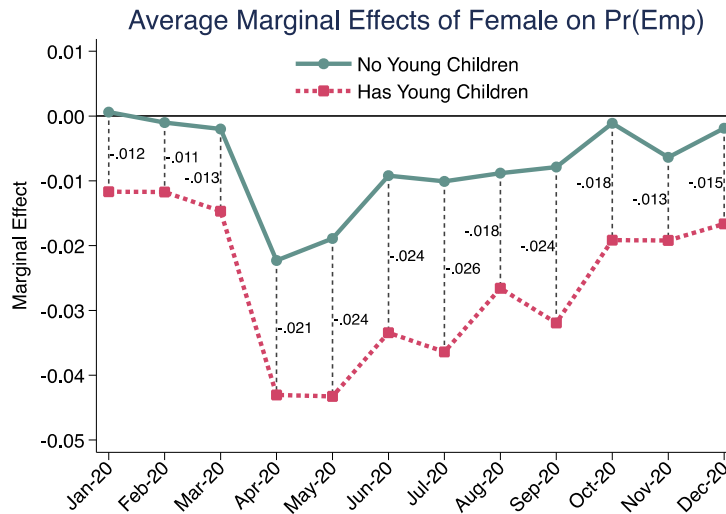
Average Marginal Effects of Female on Pr(Emp)

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the average marginal effects of being a female, with or without young children, on the probability of being employed. Each point can be read as follows: on average, for a certain month and young children status, being a woman increases/decreases the employment probability by the size of the plotted point.

To determine the magnitude of these figures, we compare what happened from March to April. In March, the female AME for those without young children was nearly zero, indicating there was no significant female penalty in the employment likelihood within that group. In April, the AME dropped sharply, to -0.022, indicating that, on average, women without young children had a probability of being employed of about two percentage points less than that of men. Within the group with young children, the drop in the AME was more pronounced. It went from -0.015 to -0.043, a difference of almost 3 percentage points. In summary, on average, mothers of young children began to experience a probability of being employed that was almost three percentage points lower than that of fathers of young children.

We further perform robustness checks using a sample containing only those employed and unemployed, excluding the individuals out of the labor force. We keep the same strategy of running monthly regressions separately for individuals with and without young children, using the same variables as our main exercise. In addition to the linear probability models, we also run logistic regressions for this sample.[10] The results are presented in the Appendix. For both the LPM and logistic models, the AMEs behave similarly to our main exercise. Additionally, the AME values are broadly similar in both models, though we can reject the

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[10]Due to the lack of information on industry and occupation for individuals out of the labor force, we were unable to apply logistic regressions to the enlarged sample of all individuals in the labor force used in the LPM analysis.

equality of the two female dummies at 10 percent the level of significance for some months rather than at 5 percent for all months as in the LPM exercise.[11]

IV. POTENTIAL ECONOMIC COSTS: ANALYTICAL ANALYSIS

We now estimate the potential economic costs of the extra employment loss suffered by mothers of young children and women in general. A two-step analysis is performed. First, we create a counterfactual aggregate employment series assuming that women with young children had the same probability of keeping their jobs as women without children (relative to the men with similar children status). We account for changes in employment across combinations of industries, occupations, and levels of education. Second, using a model-based analysis, we use the counterfactual series of employment to quantify the output cost of employment gender gaps that emerged since the onset of the crisis. We then extend the exercise to simulate the output cost associated with the increase in the employment gender gap experienced also by women without young children (assuming that all women had the same probability of keeping their jobs as men with similar occupations, industries, level of education and children status since the crisis began).

A. Counterfactual Employment Analysis

We construct two counterfactual aggregate employment series for women that simulate two distinct scenarios in terms of women's employment. To do so, we draw on the results of the empirical analysis. The results point to generalized gender differences in employment growth, but much greater among those with young children at home. Therefore, we assume that the observed widened gender gaps can be broken down into two parts. The first one is observable among workers with and without young children and comes from factors other than the extra childcare needs or other factors related to the presence of children. We call this part the "general gap." The second part is observed exclusively among those with young children that has become particularly accentuated as school closures were imposed in most part of the country.[12] We call this second part the "extra childcare-need gap." The total gender gap in employment growth is interpreted as the sum of the "general gap" and the "extra childcare-need gap."

The first counterfactual series simulates the employment trajectory of women with young children as women with young children have experienced the same employment impact as women without young children relative to their male groups. In practice, we create this series by assuming that the "extra childcare-need gap" would be zero, and therefore the gender gaps among workers with young children would be equal to the ones we observe among workers

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[11]We also estimated our main regression specification separately for those with young children between 0-5 and 6-12 years old. We did not find any significant differences between these groups.

[12]Using data from the Education Week Tracker that covers 907 school districts including the 100 largest schools district in the United States, and the largest district in each state. We find that in August, 68 percent of students were enrolled in remote learning, 19 percent in hybrid learning, and 13 percent in full in-person schools. In September, the distribution was 73 percent in remote learning, 14 percent in hybrid, and 13 percent full in-person. https://www.edweek.org/leadership/school-districts-reopening-plans-a-snapshot/2020/07

without young children (this is done by adjusting only the employment of women with young children). The second counterfactual exercise simulates female employment growth as if the pandemic had affected women and men proportionately in the same way. In other words, this series is created by considering that gender gaps in employment growth would be zero.

Formally, for each month and gender, we group workers according to their industry, occupation, level of education, and young children status.[13] Let $E_{g,i,o,e,k,t}$ be the employment of the subgroup characterized by the gender g, industry i, occupation o, education e, young children status k, in month t. Assume that $g \in \{m, f, c\}$, where m means actual male workers, f means actual female workers, and c means counterfactual female workers, that we want to generate. Then, for each possible subgroup, the employment growth $G_{g,i,o,e,k,t}$ up to a given month considering January 2020 ($t = 0$) as the starting point is given by

$$G_{g,i,o,e,k,t} = \frac{E_{g,i,o,e,k,t}}{E_{g,i,o,e,k,0}} . \tag{2}$$

From the above growth rates, we can define the actual ($GAP^A_{i,o,e,k,t}$) and counterfactual ($GAP^C_{i,o,e,k,t}$) gender employment growth gaps, respectively, as

$$GAP^A_{i,o,e,k,t} = G_{m,i,o,e,k,t} - G_{f,i,o,e,k,t} , \tag{3}$$

$$GAP^C_{i,o,e,k,t} = G_{m,i,o,e,k,t} - G_{c,i,o,e,k,t} , \tag{4}$$

where $G_{c,i,o,e,k,t}$ is the counterfactual female employment growth that we want to generate.

In the first experiment, our counterfactual series aim to simulate the growth in employment of women with young children as if women with young children have experienced similar employment trends as women without young children. Conceptually, we estimate it by equating the counterfactual gender gap among those with young children ($GAP^C_{i,o,e,1,t}$) to the actual gender gap within those without young children ($GAP^A_{i,o,e,0,t}$):

$$GAP^C_{i,o,e,1,t} = GAP^A_{i,o,e,0,t} . \tag{5}$$

After some simple algebraic manipulation, we obtain the following intuitive expression for the counterfactual female employment:

$$E_{c,i,o,e,1,t} = E_{f,i,o,e,1,0}\left(G_{m,i,o,e,1,t} - (G_{m,i,o,e,0,t} - G_{f,i,o,e,0,t})\right), \tag{6}$$

---

[13]To keep a reasonable amount of observations in each possible bin, we consider a college degree indicator for education level, a social indicator for industries, and a teleworkable indicator for occupations.

which states that the counterfactual female employment is equal to the employment growth rate of men with young children minus the actual employment gender gap for those without young children, weighted by the women employment distribution in January 2020 ($t = 0$), where the right-hand side of the above equation is fully observable in the data.

Last, we aggregate the female counterfactual employment $E_{c,t}$ by summing over the female employment of women without children, from the data, and the counterfactual employment of women with children, calculated in equation (6). Therefore, for each month, an aggregated counterfactual series can be calculated by

$$E_{c,t} = \sum_{i,o,e} E_{c,i,o,e,1,t} + \sum_{i,o,e} E_{f,i,o,e,0,t} \,. \tag{7}$$

The second counterfactual series, as discussed, intends to simulate equal employment fluctuations among women and men. This is done by making the counterfactual gaps in gender employment growth equal to zero, that is, $GAP^C_{i,o,e,k,t} = 0$ for all combination of characteristics. By plugging the gap definition, equation (4), into the previous equality, we find that the counterfactual female employment series can be written as

$$E_{c,i,o,e,k,t} = E_{f,i,o,e,k,0} \times G_{m,i,o,e,k,t} \,, \tag{8}$$

where again, by construction, the actual and counterfactual series are equal in $t = 0$ for all characteristics. As before, all elements of the right-hand side of the above expression are observable in the data. But now we are constructing a new series for all female workers, regardless of the young children status. Then, the monthly aggregated series is given by

$$E_{c,t} = \sum_{i,o,e,k} E_{c,i,o,e,k,t} \,. \tag{9}$$

The results show that without the extra childcare burden, women's employment would have been on average 1.2 percentage points higher between April and December (left panel of Figure 11). The potential gains are heterogeneous across months, ranging from almost 2.2 p.p. in May to 0.17 p.p. in December. By closing the entire increase in the gender employment gap to the pre-crisis period, we find that women's employment would be 2.6 p. p. higher, on average, over the same period (right panel of Figure 11). The most considerable gains would have been in June (4.12 p.p.) and July (4.73 p.p.). As a result, by closing only the "extra childcare-need gap" we explain, on average, 45 percent of the "general gap" (1.2/2.6).[14]

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[14]During June-August, many summer camps, which kids usually attend when they are out of school, were also closed due to the pandemic and related lockdown measures.

Figure 11. Actual and Counterfactual Women's Employment Fluctuations

Employment Cumulative Growth
Same Employment Gender Gap For Women With And Without Young Children

Employment Cumulative Growth
Women And Men Affected At The Same Rate
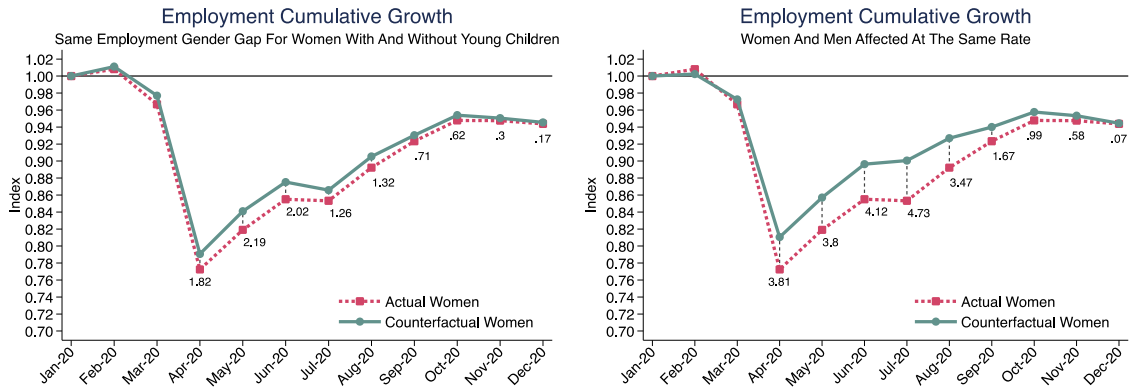
Sources: Current Population Survey (CPS); authors' calculations.
Notes: On the left panel, we are plotting the employment cumulative growth using the counterfactual series calculated from equation (7). On the right panel, we are plotting the employment cumulative growth using the counterfactual series calculated from equation (9). All series are plotted using January 2020 as the reference point.

The potential gains from closing the entire increase in the gender gap are substantial. To better understand who would be benefiting more, we decompose the total employment gains into the gains from women with and without young children (Figure 12). We find that, on average, women with young children would account for 60 percent of the potential employment gains from April to December. This is a remarkable result since, in our sample, women with young children represent only 25 percent of total female employment.

Figure 12. Decomposition of Potential Gains When Closing the Entire Employment Gender Gap Increase

Decomposition of Potential Employment Gains
Women And Men Affected At The Same Rate
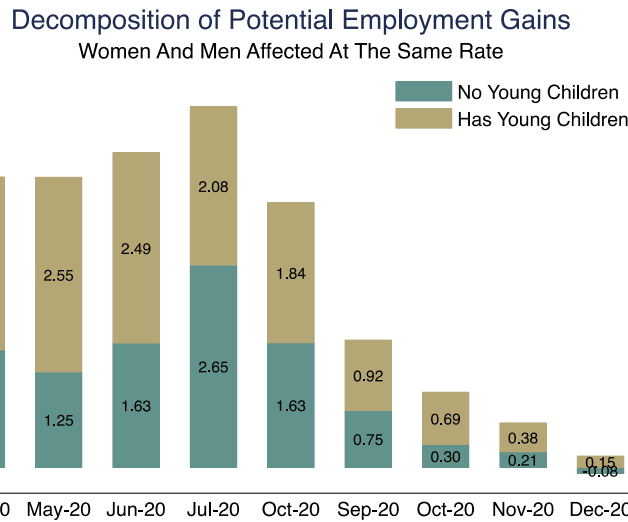
Sources: Current Population Survey (CPS); authors' calculations.
Notes: For each month, the sum of the numbers reported on each bar is equal to the spread value reported in the corresponding month on the right panel of Figure 11.

B. Economic Model: Description and Calibration

To assess the output impact of the pandemic-driven rise in the employment gender gap, we use a production-function model to simulate counterfactual output scenarios throughout the pandemic. In each month t, we assume that total output Y_t is produced using capital K_t and labor L_t as inputs into a Cobb-Douglas production function given by

$$Y_t = A_t K_t^\alpha L_t^{1-\alpha}, \tag{10}$$

where A_t is total factor productivity (TFP) and α is capital's share of output. The labor input is composed of women's and men's total hours worked combined into a CES aggregator given by

$$L_t = \left(\phi_{m,t} H_{m,t}^\rho + \phi_{f,t} H_{f,t}^\rho\right)^{1/\rho}, \tag{11}$$

where $H_{m,t}$ ($H_{f,t}$) is men's (women's) total hours worked, $\phi_{m,t}$ ($\phi_{f,t}$) is the weight on men's (women's) hours, and ρ captures the elasticity of substitution between the worked hours of men and women. We assume that $\phi_{m,t} + \phi_{f,t} = 1$. Note that we are allowing the hours' weights to vary over time. When simulating the model, our main focus is on the transition of output cumulative growth starting in January 2020 ($t = 0$), which can be written as

$$g_t = \frac{Y_t}{Y_0} = \frac{A_t}{A_0} \left(\frac{K_t}{K_0}\right)^\alpha \left(\frac{L_t}{L_0}\right)^{1-\alpha}. \tag{12}$$

The calibration of the model's parameters is done for the United States and follows the standards of the literature. We set the capital share α to 0.36, which is the 2019 figure estimated by the Conference Board Total Economy Database (TED).[15] The parameter ρ is set to 0.5 to match an elasticity of substitution of 2.0 following the estimates from Ostry and others (2018). We experiment with other values for the elasticity of substitution to assess the sensibility of our results.

To calibrate the total hours' weights in the CES aggregator, we first assume that workers are paid their marginal product every month, i.e., $w_{m,t} = \partial Y_t / \partial H_{m,t}$ and $w_{f,t} = \partial Y_t / \partial H_{f,t}$ for all t, where $w_{m,t}$ and $w_{f,t}$ are the hourly wage rates of men and women, respectively. Then, by solving for the women's weight from the female-to-male wage ratio, we get that

$$\phi_{f,t} = \frac{1}{\left(\dfrac{w_{m,t}}{w_{f,t}}\right)\left(\dfrac{H_{m,t}}{H_{f,t}}\right)^{1-\rho} + 1}. \tag{13}$$

---

[15]For the source, refer to https://conference-board.org/data/economydatabase.

The monthly hour ratios are calculated from the CPS microdata. The wage rate ratios are calculated using the median usual weekly earnings of full-time workers from the BLS. As the BLS only releases these numbers quarterly, we repeat the same value for all months in the same quarter.[16] Then, we can feed these data into equation (13) to backout $\phi_{f,t}$ and, consequently, the men's weight as $\phi_{m,t} = 1 - \phi_{f,t}$.

Finally, we calibrate the TFP series so that the model replicates the monthly growth rate of output from the IHS Markit Monthly Real GDP Index.[17] We use equation (12) to solve for the monthly TFP growth as a function of output, capital, and labor growth. The output growth data is given, and the labor growth series is calculated from the total hours' data and the already calibrated parameters. For capital growth, we make the conventional short-term assumption that capital is fixed and set its growth factor to 1 every month. Then, we can feed the output and labor figures into equation (12) to backout the monthly TFP growth series.[18]

C. The Output Costs of Gender Gaps

We conduct two different simulations by feeding our model with the counterfactual employment series from Section V.A. First, by using the counterfactual employment series for women generated by equation (7), we simulate output growth in a counterfactual scenario where women with young children have faced a similar employment trend as women without young children. Second, by using instead the counterfactual employment series generated by equation (9), we simulate output growth in a scenario where women and men would have been affected by the crisis at the same rate. Note that, in both experiments, we are considering the men's employment series as in the data.

As described in the previous section, the model's labor input depends on the total hours worked of men and women. However, when running the simulations, we are only varying the female employment component of the labor input. To address this issue, we use the fact that the total hours worked is equal to the product of average worked hours and total employment. Formally, women's total hours can be described as $H_{f,t} = h_{f,t}E_{f,t}$, where $h_{f,t}$ is the average worked hours and $E_{f,t}$ is the employment level. Therefore, to generate the counterfactual total hours series for women, we simply substitute the actual employment component with the counterfactual one, keeping average hours worked as in the data. Formally, the counterfactual women's total hours worked is given by $H_{c,t} = h_{f,t}E_{c,t}$, where $E_{c,t}$ is calculated from equations (7) or (9) depending on the experiment.

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[16]The male-to-female wage rate ratios for each quarter are as follows: 1.239 for Q1; 1.190 for Q2; 1.233 for Q3; 1.193 for Q4. For the source, refer to https://www.bls.gov/charts/usual-weekly-earnings/usual-weekly-earnings-over-time-total-men-women.htm.

[17]For the source, refer to https://ihsmarkit.com/products/us-monthly-gdp-index.html.

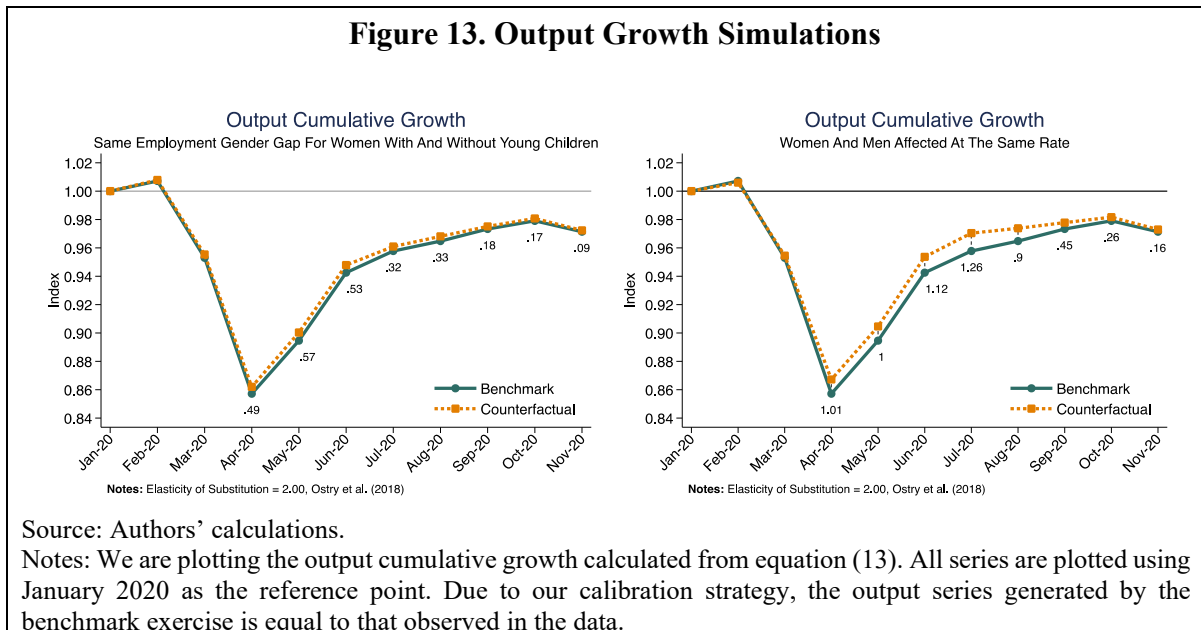[18]Note that this calibration strategy ensures by construction that the output series generated by the model is equal to that observed in the data when we feed the model with actual total hours worked.

We calculate the total percentage loss in output, over the April-November period, generated by the benchmark relative to the counterfactual simulations. Note that the benchmark is the economy calibrated to replicate the data. To formally specify such a metric, let "B" and "C" be the labels of the variables of interest in the benchmark and counterfactual exercises, respectively. Then, the relative total percentage loss can be defined as

$$LOSS = 1 - \frac{\sum_{t=4}^{11} Y_t^B}{\sum_{t=4}^{11} Y_t^C} = \frac{\sum_{t=4}^{11}(Y_t^C - Y_t^B)}{\sum_{t=4}^{11} Y_t^C} = \frac{\sum_{t=4}^{11}(g_t^C - g_t^B)}{\sum_{t=4}^{11} g_t^C}, \tag{14}$$

where the last equality comes from dividing the numerator and denominator by the January output level. The loss metric is expressed by the numbers plotted in Figure 13. The results show that the total actual output, over the April-November period, was 0.36 percent lower relative to the scenario in which women with young children (relative to men with young children) were to face the same probability of keeping their jobs compared to women without young children (relative to men without young children). Also, relative to the scenario in which all women and men were affected by the crisis at the same rate, the total output was 0.81 percent lower during the same period.

Figure 13. Output Growth Simulations

Source: Authors' calculations.
Notes: We are plotting the output cumulative growth calculated from equation (13). All series are plotted using January 2020 as the reference point. Due to our calibration strategy, the output series generated by the benchmark exercise is equal to that observed in the data.

We finally perform a robustness check to assess the sensibility of our results to different values of the elasticity of substitution between women's and men's total hours worked. Our benchmark value was set to 2, following Ostry and others. (2018). We now consider two alternative figures: a larger one equal to 4.33 (Albanesi, 2020) and a smaller one equal to 1.7

(Ghosh, 2018). Larger (smaller) values imply a larger (smaller) degree of substitution between men's and women's total hours worked.[19]

As expected, when we increase the degree of substitution between men's and women's total hours worked, the total output loss would be lower, equal to 0.34 percentage points, compared to 0.36 percentage points in the benchmark (left panel of Figure 14). For the scenario in which women and men are affected ate the same rate, the total output loss is estimated at 0.78 percentage points, 0.03 percentage points less than the benchmark figure (right panel of Figure 14). Alternatively, when the elasticity of substitution is lower, implying a larger complementary between men's and women's hours worked, the loss is slightly higher (Figure 15). The total output loss is estimated at 0.36 percentage points in the first scenario and 0.82 percentage points in the scenario where women and men are affected at the same rate.

Figure 14. Robustness Checks, ES = 4.33

Source: Authors' calculations.
Notes: We are plotting the output cumulative growth calculated from equation (13). All series are plotted using January 2020 as the reference point. Since we are not recalibrating the parameters when varying the elasticities of substitution, the output series generated by the benchmark exercise is no longer necessarily equal to that observed in the data.

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[19]We do not recalibrate the parameters when performing the robustness exercises with different elasticities of substitution. Therefore, in these cases, the output series generated by the benchmark exercise is no longer necessarily equal to that observed in the data.

Figure 15. Robustness Checks, ES = 1.70
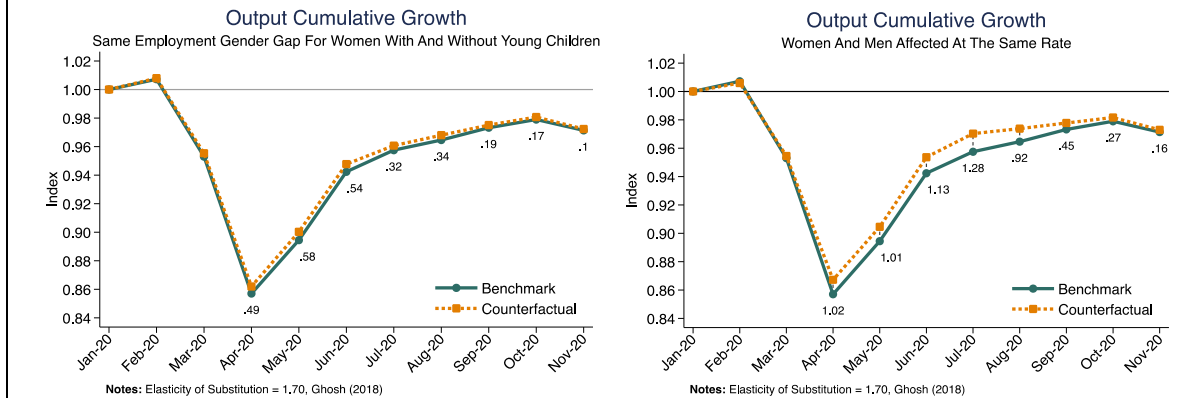
Source: Authors' calculations.
Notes: We are plotting the output cumulative growth calculated from equation (13). All series are plotted using January 2020 as the reference point. Since we are not recalibrating the parameters when varying the elasticities of substitution, the output series generated by the benchmark exercise is no longer necessarily equal to that observed in the data.

V. CONCLUSION

In this paper, using monthly household survey data for the United States, we analyze employment losses by population group over the first nine months of the COVID-19 crisis. Controlling for industry, occupation, and education level, we find that women with young children have been the most affected by the crisis. As schools closed at the onset of the crisis, this group of women experienced larger employment losses than other women and men with or without young children. These women also witnessed a milder recovery in employment than others over the subsequent months. Further, the less educated among these women experienced greater job losses. This suggests that the risk of infection and the measures adopted to contain it, including school closures, increased both gender and income inequalities. In addition, race seems to matter. In fact, African-American women with young children have lost more jobs than other workers.

Beyond the additional childcare burden, which account for 45 percent of the increase in the employment gender gap during the crisis, other factors also played a role. We find that women without young children have also experienced greater employment loss than men without young children working in similar industries and occupying jobs with same level of education. Another interesting finding that would require further investigation is that men with young children employed in social industries have kept their jobs more than other groups.

Next, we use empirical analysis to calculate a counterfactual series of female employment where women with young children had the same opportunities to hold their jobs as other women (relatively to men with similar children status). Feeding this counterfactual series into a production-function model, we find that the extra-childcare burden on female employment induced by the pandemic and measures to contain it, such as school closures, may have reduced total U.S. output by 0.36 percent between April and November 2020. This

estimate neither includes other factors such as, for example, the job losses at schools themselves and employment spillovers to other (non-education) sectors, nor the possible reduction of children's human capital and future earnings (Fuchs-Schündeln and others., 2020), in particular for children of poor families (Agostinelli and others, 2020).

Our findings point to the importance of limiting the extra childcare on families, which is mostly affecting women, and prioritize measures that could alleviate such burden such as early reopening of schools. This requires investing in infrastructure and procedures to ensure a safe and sustainable reopening of schools, which should be a priority for governments. Decisions about vaccination and related priority groups should also take into consideration the urgency of school reopening. This is particularly important for countries where vaccines may not be rolled out for some time, such as in developing countries that are still in the process of procuring vaccines and making decisions regarding how to prioritize vaccine distribution.

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APPENDIX I: SAMPLE CHARACTERISTICS

Table 1. Employment Summary Jan-20									
	No Young Children			**Has Young Children**			**Total Sample**		
	% M	% F	Share F	% M	% F	Share F	% M	% F	Share F
Occupation									
Non-teleworkable	67.7	54.8	41.9	64.8	55.7	43.9	67.0	55.0	42.4
Teleworkable	32.3	45.2	55.5	35.2	44.3	53.4	33.0	45.0	54.9
Total	*100*	*100*	-	*100*	*100*	-	*100*	*100*	-
Industry									
Non-social	54.8	34.1	35.7	60.7	33.0	33.1	56.3	33.9	35.0
Social	45.2	65.9	56.5	39.3	67.0	60.8	43.7	66.1	57.6
Total	*100*	*100*	-	*100*	*100*	-	*100*	*100*	-
Education									
No college degree	64.8	58.8	44.7	58.0	54.2	46.0	63.1	57.6	45.0
Has college degree	35.2	41.2	51.0	42.0	45.8	49.8	36.9	42.4	50.7
Total	*100*	*100*	-	*100*	*100*	-	*100*	*100*	-

Sources: Current Population Survey (CPS); authors' calculations.

Table 2. Employment Distribution by Young Children and Marital Status Jan-20		Men (%)	Women (%)	Women (% share)
No young children	Not married	39.7	41.0	48.1
	Married	35.4	33.6	46.0
	Sub-total	*75.0*	*74.6*	-
Has young children	Not married	3.2	8.0	69.1
	Married	21.8	17.4	41.7
	Sub-total	*25.0*	*25.4*	-
Total		*100*	*100*	-

Sources: Current Population Survey (CPS); authors' calculations.

APPENDIX II: ADDITIONAL DATA ANALYSIS

Figure 1. Employment Fluctuations in Teleworkable Occupations
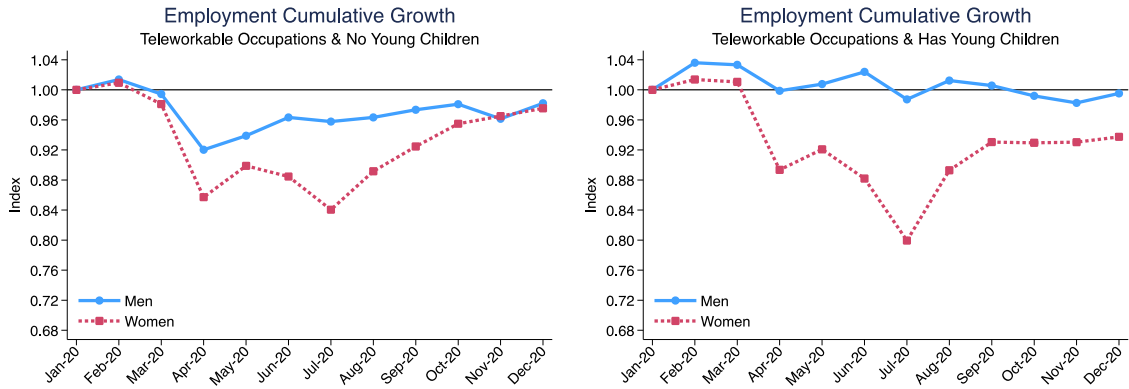
Employment Cumulative Growth
Teleworkable Occupations & No Young Children

Employment Cumulative Growth
Teleworkable Occupations & Has Young Children

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020.

Figure 2. Employment Fluctuations in Non-social Industries

Employment Cumulative Growth
Non-Social Industries & No Young Children

Employment Cumulative Growth
Non-Social Industries & Has Young Children

Sources: Current Population Survey (CPS); authors' calculations.
Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020.

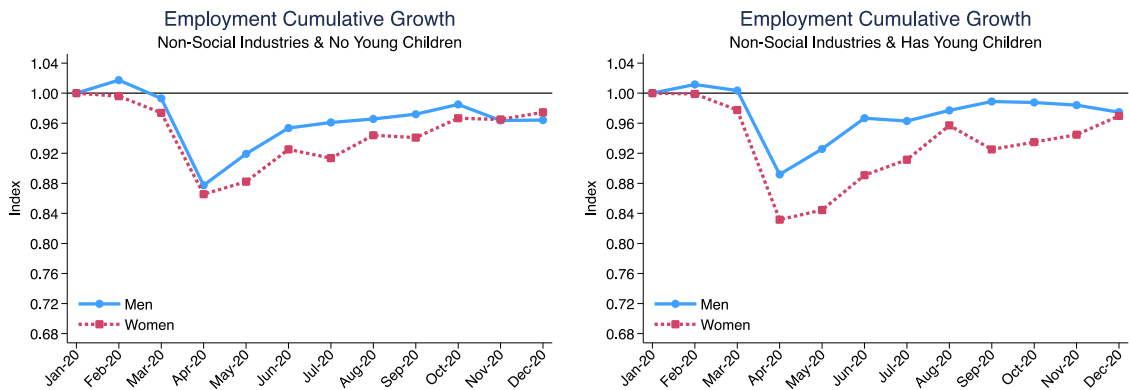## Figure 3. Employment Fluctuations by Race

Sources: Current Population Survey (CPS); authors' calculations.

Note: We are plotting the employment cumulative growth using January 2020 as the reference point. Formally, each point represents the ratio between the employment level of the current month and the corresponding value in January 2020.
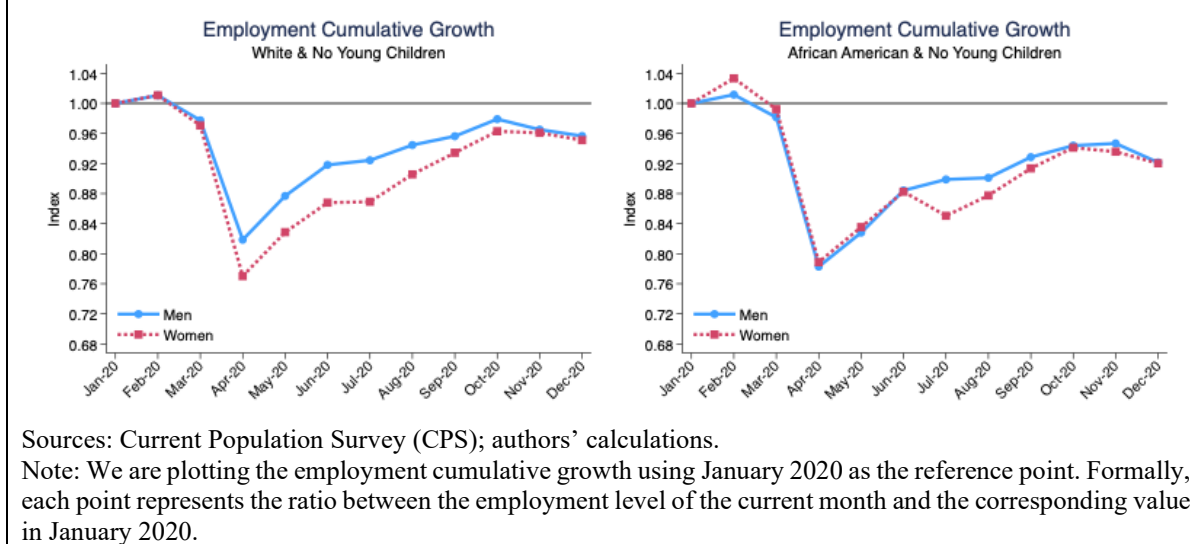
APPENDIX III: EMPIRICAL ROBUSTNESS EXERCISES

Figure 4. Linear Probability Models

Sources: Current Population Survey (CPS); authors' calculations.

Note: On the left panel, we are plotting the average marginal effects of being a female, with or without young children, on the probability of being employed. Each point can be read as follows: on average, for a certain month and young children status, being a woman increases/decreases the employment probability by the size of the plotted point. On the right panel, we are plotting the p-values of the hypothesis tests in which we test for the equality of the two female dummy coefficients. The null hypothesis is that the two coefficients are equal. The tests are performed separately for each monthly regression.
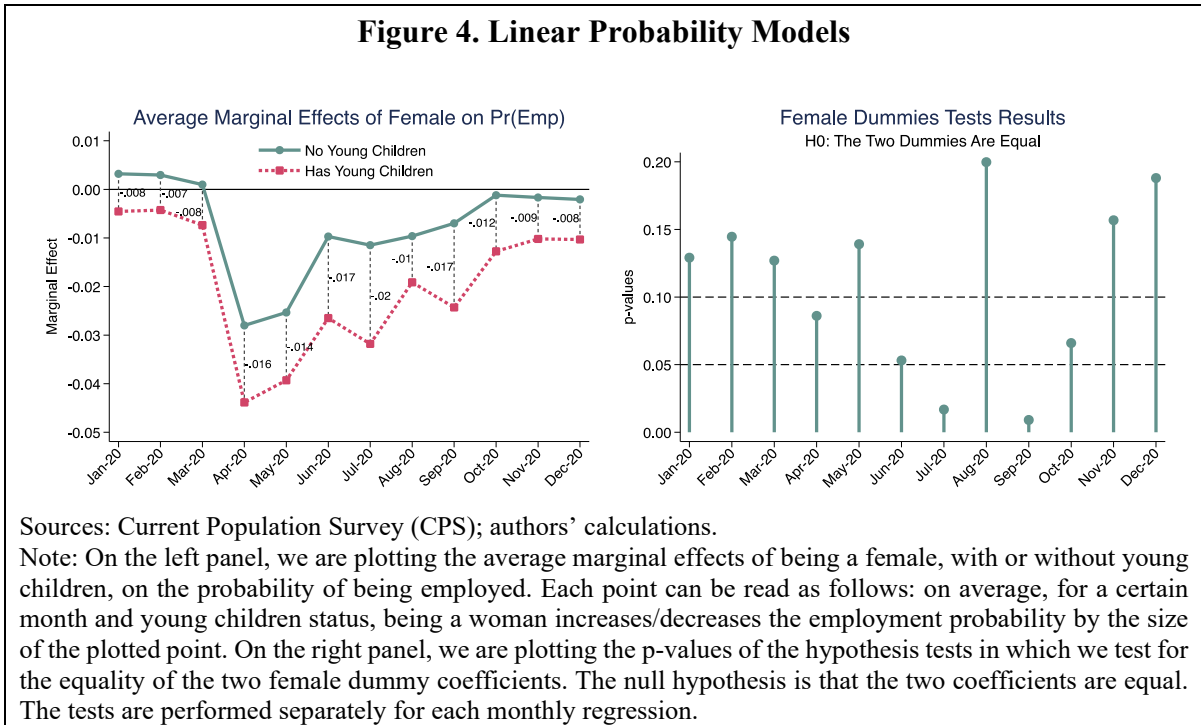
Figure 5. Logistic Regressions

Sources: Current Population Survey (CPS); authors' calculations.

Note: On the left panel, we are plotting the average marginal effects of being a female, with or without young children, on the probability of being employed. Each point can be read as follows: on average, for a certain month and young children status, being a woman increases/decreases the employment probability by the size of the plotted point. See Long and Freese (2014) for references on the marginal effects methodology for categorical dependent variables in non-linear regressions. On the right panel, we are plotting the p-values of the hypothesis tests in which we test for the equality of the two female dummy coefficients. The null hypothesis is that the two coefficients are equal. The tests are performed separately for each monthly regression.