From Mancession to Shecession: Women's Employment in Regular and Pandemic Recessions*

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Abstract

We examine the impact of the global recession triggered by the Covid-19 pandemic on women's versus men's employment. Whereas recent recessions in advanced economies had a disproportionate impact on men's employment, giving rise to the moniker "mancessions," we show that the pandemic recession of 2020 was a "shecession" with larger employment declines among women in most countries. We examine the causes behind this pattern using micro data from several national labor force surveys, and show that both the composition of women's employment across industries and occupations as well as increased childcare needs during closures of schools and daycare centers made important contributions. Gender gaps in the employment impact of the pandemic arise almost entirely among workers who are unable to work from home. Among telecommuters a different kind of gender gap arises: women working from home during the pandemic spent more work time also doing childcare and experienced greater productivity reductions than men. We identify two key challenges for future research. First, why is the pandemic gender gap pervasive, i.e., why did women experience larger employment reductions than men even after accounting for industry/occupation and childcare effects? Second, how will the pandemic shape gender equality in a post-pandemic labor market that will likely continue to be characterized by pervasive telecommuting?

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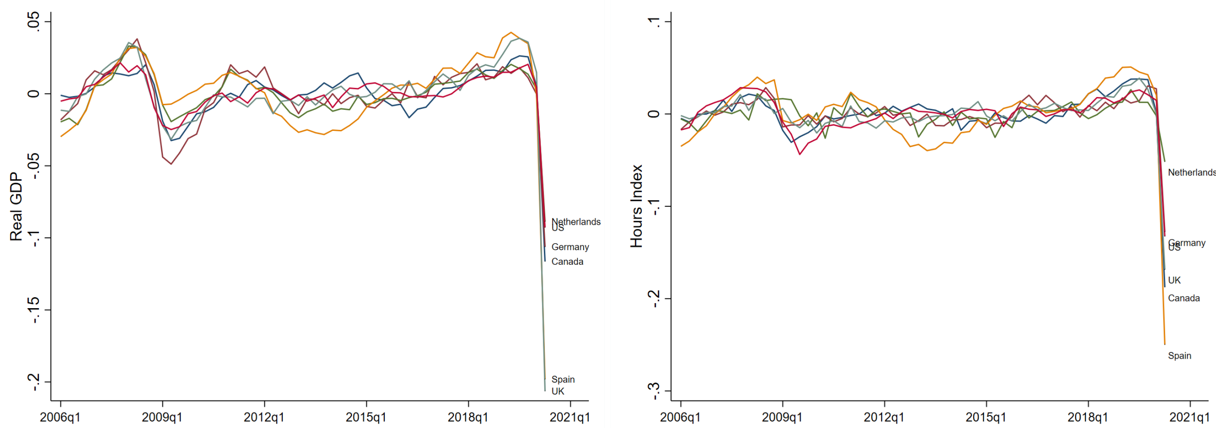
1 Introduction

The Covid-19 pandemic has resulted in the sharpest global economic downturn since the Great Depression. Figure 1 displays deviations from long term trends in GDP and aggregate hours worked in the United States, Canada, Germany, the Netherlands, Spain, and the United Kingdom from 2006 until the second quarter of 2020.[1] In each of these countries, the drop in output and labor supply during the pandemic recession is much larger than during any previous downturn in this period, at least twice as large even compared to the Great Recession of 2007 to 2009. Understanding the nature and consequences of this massive economic shock is a central task for economic research.

Figure 1: The Pandemic Recession in Six Countries



(a) GDP, cyclical component (b) Hours Worked, cyclical component

Notes: See Appendix for data sources. Hours index is the index (=100 in 2006) of total hours of adult workers (20-64) in the economy. Seasonally adjusted quarterly real GDP and hours index (2006 Q1-2020 Q2) are HP filtered with smoothing parameter 1600 and cyclical components are reported.

At the onset of the crisis, Alon et al. (2020a) predicted that beyond its cause and magnitude, a key difference between the pandemic recession and others that preceded it would lie in its impact on women's employment. Recent pre-pandemic recessions have usually been "mancessions" in which men lost more jobs than women. The prediction by Alon et al. that the pandemic recession would be a "shecession" with larger employment losses for women was based on two observations. First, while regular recessions heavily affect sectors such as construction and manufacturing in which many men work, it became quickly apparent that the pandemic recession would have its biggest impact

[1] The figure depicts the cyclical components of both GDP and hours worked. Appendix Figure A2 shows the raw data.

on sectors such as hospitality and tourism with high female employment shares. Second, the pandemic also led to school and daycare closures that massively increased parents' childcare needs, and given that mothers provide a much larger share of childcare than fathers do, this would constrain women's ability to work more than men's.

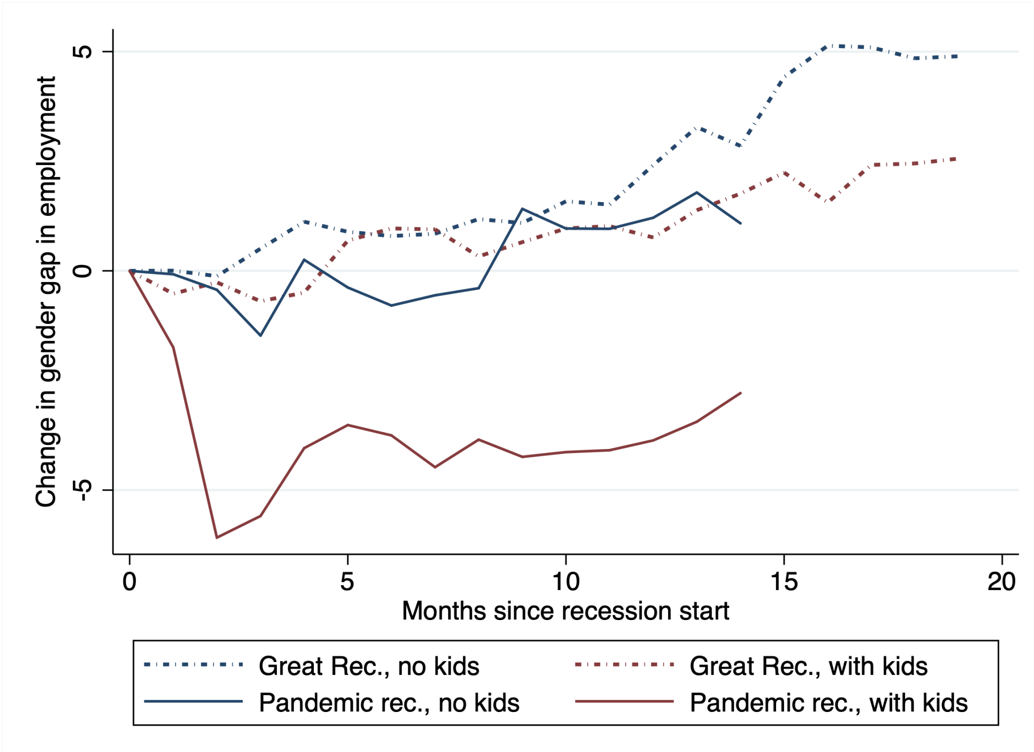
With the benefit of hindsight, in this paper we provide a comprehensive empirical assessment of the role of women's employment in the pandemic recession of 2020. We argue that the evidence largely confirms the expectation of a larger impact on women in general and on working mothers in particular. As an illustration for the case of the United States, Figure 2 reports changes in the employment gap (the difference between the employment rate of women and men) during the pandemic recession of 2020 compared to the Great Recession of 2007–2009.[2] During the Great Recession, women's employment increased compared to men, with gains gradually building as the recession progressed. This is the typical pattern of a mancession that puts more men than women out of employment. In the pandemic recession, in contrast, women's employment declined relative to that of men. For women without children, this decline was mild, but among women with children the drop in employment exceeded 5 percentage points two months into the recession compared to men with children. Employment losses declined somewhat during the summer of 2020, but expanded again in the fall.

Expanding on this evidence, we document the impact of the pandemic recession on women's versus men's employment across advanced economies; we use micro data to assess the role of childcare needs, industry and occupation effects, and other factors in generating gender differences; and we assess how the gendered impact of the crisis matters for aggregate outcomes during the recession and for the evolution of gender inequality in the labor market beyond. We find that the pandemic recession had an unusually large impact on working women across a large set of countries, but also that there is wide heterogeneity in the magnitude of the impact and the role of different channels underlying these impacts. The heterogeneity that we observe is informative for the role that policies and institutions play in shaping the economic impact of the recession. We also point to evidence that the pandemic recession will have long lasting effects on the labor market. In particular, the recession is likely to result in a substantial rise in employment flexibility in the post-pandemic "new normal," which has the potential to greatly benefit many working women.

To provide a baseline to compare the pandemic recession to, the first step in our analysis

[2] An analogous figure reporting hours worked by gender is provided in the Appendix (Figure A4).

Figure 2: Change in Gender Gap in Employment in the United States during the Great Recession and the Pandemic Recession



Notes: The y-axis reports cumulative log point changes in the employment gender gap from the start of each recession (difference between women's and men's employment, negative numbers denote a decline in women's relative employment). Sample includes all civilians ages 25 to 55 who are either employed, unemployed, or not in the labor force. Employment series are seasonally adjusted by group from January 2000 to October 2020. Great Recession corresponds to November 2007 to June 2009. The pandemic recession corresponds to February 2020 to April 2021. Workers "with kids" are those who have at least one own minor child (ages 0 to 17) residing in the same household.

is to use aggregate data for 28 advanced economies to characterize the impact of regular, pre-pandemic business cycles on women's versus men's employment. Similar to what Doepke and Tertilt (2016) established for the United States, we find that with few exceptions regular recessions are mancessions in these countries, i.e., during a typical business cycle downturn, male labor supply falls by more than female labor supply. We also show that differences in the cyclical volatility between industries with high female versus male employment shares play an important role in accounting for this pattern.

Turning to the pandemic recession, we find that in most countries the current recession is a shecession, i.e., declines in employment and hours worked are larger among women. Moreover, in the few countries where the pandemic had a larger impact on men, the relative impact on women's labor market is usually more severe than what would be expected based on earlier recession. Thus, a disproportionate impact on working women is a common feature of the pandemic recession that is shared among a large set of countries.

To learn more about the causes and consequences of this shecession, we turn to micro survey data from the six countries represented in Figure 1: the United States, Canada, Germany, the Netherlands, Spain, and the United Kingdom. These countries represent a wide range of experiences in terms of the impact of the pandemic recession on the labor market. In the United States, Canada, and Germany there is a substantial gender gap in the response of hours worked. In the United States there is also a large gender gap in terms of employment changes, but not so in Germany, a first indication that policy responses (such as more generous employment protection and furlough in Germany) play an important role during the crisis. In the Netherlands, Spain, and the United Kingdom, gender gaps in changes in both employment and hours worked are generally small.

Information on individual characteristics in the micro data allow us to assess the role of childcare needs, industry and occupation, and other factors in generating gender differences during the pandemic recession. Regarding childcare, we find that the impact on the gender gap is largest among parents with school-age children, pointing to the role of school closures. As Figure 2 suggests, in the United States the impact of the childcare channel is large. We find large gender gaps in labor supply response among parents of school-age children, even in countries where the overall gender gap in the impact of the pandemic is small, such as Spain. Beyond childcare, industry and occupation effects account for another sizeable part of the gender gap in the impact of the crisis. Nevertheless, childcare, industry, and occupation are not the only channels at work: even when controlling for industry and occupation and considering only workers without children, we still find large gender gaps in several countries. For the United States, a decomposition analysis shows that the childcare and industry/occupation channels each account for a little less than 20 percent of the gender gap in terms of hours worked, with the remainder due to other factors. Understanding these additional factors behind the pervasive gender gap in the pandemic recession is an important challenge for future research.

We also analyze other dimensions of heterogeneity. A factor that matters a lot in the United States, Canada, and Spain is single parenthood: both hours and employment decline by more for single compared to married mothers. Much of the single-married divide disappears when controlling for industry and occupation, implying that the kind of jobs that single mothers hold matter. We do not find significant differences between married and single mothers in the other countries.

With regard to education, in the United States and Canada we observe larger gender gaps in the labor supply response of less educated workers. Interestingly, the opposite finding arises in Spain and the United Kingdom (countries with a small overall gender gap in the impact of the pandemic) where we find a substantial gender gap in hours changes among parents of school age children with college education, but not among less educated parents.

In the United States, it is well documented that the Black and Hispanic population was particularly strongly affected by the labor market consequences of the pandemic (e.g., Hershbein and Holzer 2021). However, we generally do not find large or statistically significant differences in the gender gap in the labor supply response between different races and ethnicities or between workers with and without a migration background. The two exceptions are Germany, where the gender gap in employment losses is larger among those with a migration background, and Canada, where we observe a similar pattern in both employment and hours.

The disproportionate impact of the pandemic recession on women's employment not only matters for the distribution of the welfare cost of the pandemic recession, but also has wider economic repercussions. Based on the analysis of Alon et al. (2020b), we argue that qualitative differences between shecessions and mancessions arise from the different dynamic behavior of women's and men's labor supply. Women's labor supply is generally more elastic than that of men, suggesting that in a shecession, lowered earning prospects after an unemployment spell are more likely to result in a persistent reduction in labor supply. A shecession also reduces households' ability to self-insure against income shocks, resulting in a stronger transmission from income shocks into consumption demand. On the other hand, since women on average work fewer hours and earn less, shecessions can be less severe in terms of GDP losses than mancessions. Overall, whether a recession affects primarily men or women clearly matters: a shecession is not just a mancession with signs reversed.

The legacy of the pandemic recession is likely to include changes in the labor market that will long outlast the recession itself. One feature of the post-pandemic new normal that is already becoming apparent now is that working from home, near universal among office workers during the pandemic, will have a permanent place in the future workplace (Barrero, Bloom, and Davis 2021). Alon et al. (2020b) argue that increased access to telecommuting and other forms of work flexibility has the potential to drastically reduce gender inequality in the labor market. The basis for this argument is that much of today's gender gap arises from the "motherhood penalty" (i.e., women's earnings start to lag behind those of men after having children). Work flexibility in general and telecommuting in particular are associated with a more equal division of childcare duties among mothers and fathers, thereby lowering the conflict for mothers between having a family and a career. Hence, if the future workplace indeed is more flexible, the motherhood penalty should shrink and so should overall gender inequality in the labor market.

Our empirical results reaffirm the notion that job flexibility is a particular benefit to working mothers. For the countries where we have information on telecommuting, we find that the gender gap in labor supply is concentrated among those that cannot telecommute. Among non-telecommuters the gender gap is especially large among parents, whereas among those who can work from home gender gaps are small regardless of whether children are present. While several recent papers (e.g., Adams-Prassl et al. 2020b) have pointed out that the ability to telecommute protects workers from job loss in the current pandemic, our findings show that it is mothers who reap the largest gains from being able to work from home.

These findings suggest that the pandemic legacy of an expanded ability to telecommute will play an important role in advancing gender inequality. Yet, there is a caveat. For the motherhood penalty to be reduced in the new normal, both mothers and fathers working from home would have to get their work done. In contrast, evidence from the pandemic suggests that combining working from home with caring for children imposes a bigger drag on mothers' compared to fathers' productivity. In the Netherlands, we find that among parents working from home during the crisis, mothers used a larger fraction of the work time to provide childcare at the same time, particularly so if they had school-age children. Other studies document that among academic researchers (where productivity can be measured using publications and new working papers) productivity declined more among women than among men during the pandemic, with the largest productivity declines among mothers of young children (Amano-Patiño et al. 2020; Ribarovska et al. 2021; Barber et al. 2021). Hence, increased work flexibility after the pandemic opens up the potential for reduced gender inequality, but the full potential for change is unlikely to be realized without shifts in additional factors, such as social norms and workplace norms, that also determine the division of labor between mothers and fathers. Understanding the evolution and interplay of these factors shaping gender inequality in the post-pandemic labor market is an important challenge for future research on the legacy of the crisis.

Our work contributes to the literature on the role of women's employment over the business cycle. Even though by now women account for the majority of the US workforce, for a long time most business cycle models have been unisex models that do not allow for gender differences. More recent studies argue that the role of women over the business cycle has substantially changed over time due to the rise in female labor force participation (Albanesi 2020; Fukui, Nakamura, and Steinsson 2019). The changed nature of business cycles also matters for policy. Bardóczy (2020) argues that the details of decision-making in the family are an important determinant of the transmission of macroeconomic shocks. Ellieroth (2019) analyzes the quantitative importance of family insurance over the business cycle using a joint-search model. Other contributions to the literature on women's employment and household decision-making within macroeconomics include Greenwood, Seshadri, and Yorukoglu (2005), Ortigueira and Siassi (2013), Doepke and Tertilt (2016), Mankart and Oikonomou (2017), Borella, De Nardi, and Yang (2018), Mennuni (2019), Olsson (2019), and Wang (2019).[3] In addition, Albanesi and Şahin (2018) and Coskun and Dalgic (2020) note the impact that the gender breakdown of employment in various industries has on the contrasting cyclicality of male and female employment. This is an important factor in the pandemic recession, since the industries hit the most by the pandemic are not those most affected by regular recessions. Finally, our work is part of the emerging literature on the impact of the Covid-19 pandemic on gender inequality in the labor market, including contributions such as Alon et al. (2020a, 2020b) and Adams-Prassl et al. (2020b). Our contribution is related in particular to Albanesi and Kim (2021), who take a similar empirical approach but focus entirely on the United States, and the studies by Dang and Nguyen (2020), Galasso and Foucault (2020), Leyva and Urrutia (2020), and Bluedorn et al. (2021) who also provide evidence across countries but without delving into detailed micro data.

In the next section, we examine the impact the pandemic recession and earlier economic downturns on women's and men's employment in 28 countries using aggregate data. In

[3]Macroeconomic studies of the policy implications of joint household decisions include Guner, Kaygusuz, and Ventura (2012), Guner, Kaygusuz, and Ventura (2020), Bick (2016), and Krueger and Wu (2019).

Section 3 we use micro data from national employment surveys to examine the sources of the gendered impact of the pandemic recession. In Section 4 we provide further results for the United States, where the gender gap in the impact of the pandemic of the recession is particularly large. In Section 5 we examine heterogeneity along the dimensions of education, race, single parenthood, and the ability to telecommute. Section 6 analyzes the impact of the pandemic on women's and men's productivity at work. In Section 7 we discuss the general lessons that can be learned from our analysis, and Section 8 concludes.

2 Aggregate Evidence across Countries

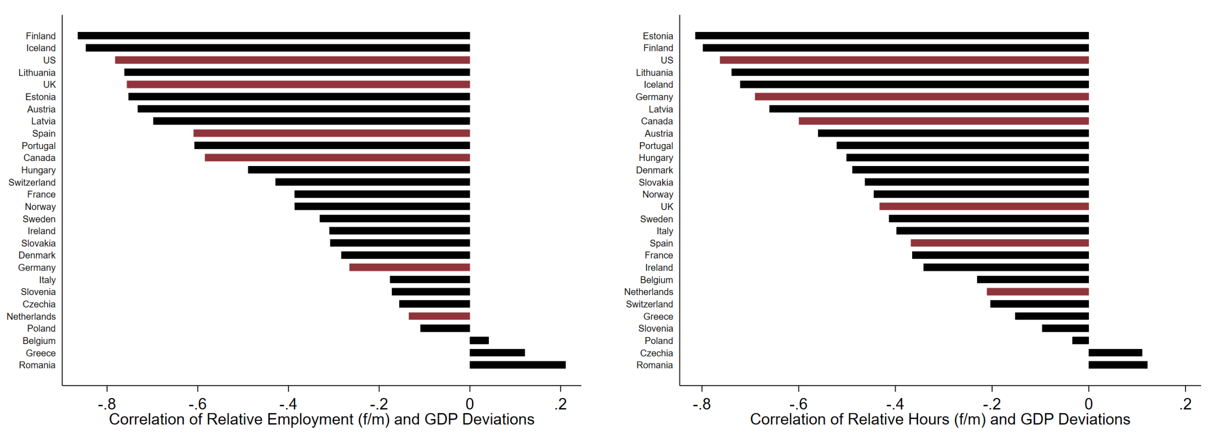
We start by providing an overview of the impact of earlier recessions and the pandemic recession on women's and men's employment across countries using aggregate data. We use data for 26 European countries from the European Labor Force Survey (EU-LFS), US data from the Current Population Survey (CPS), and Canadian data from Canadian Labor Force Survey (CLFS).

2.1 Regular Recessions

Doepke and Tertilt (2016) document that in the United States, women's labor supply is substantially less cyclical than that of men. In recessions, the labor supply of single men usually declines the most, whereas the drop in labor supply is smallest for married women. The same patterns can be observed in most countries in our data set. To characterize how labor supply varies over the cycle, we first compute the cyclical component of GDP as the difference between GDP and a Hodrick-Prescott trend. We then focus on the correlation between the cyclical component of GDP with the the ratio of women's to men's labor supply. Figure 3 shows that in most countries in our data set male labor supply is more cyclical than female labor supply. This is true both for the extensive and the intensive margin: panel (a) shows a negative correlation between the cyclical components of relative female/male employment and GDP while panel (b) shows a negative correlation between the cyclical components of relative hours and GDP. There are a few exceptions (Romania, Greece and Belgium for the correlation with relative employment, and Romania and Czechia for the correlation with relative hours), but in all these cases the correlations are small.

The literature points out two primary explanations for the countercyclicality of women's relative labor supply: the distribution of women's employment by industry and occu-

Figure 3: In Most Countries, Women's Relative Labor Supply was Countercyclical Before 2020



(a) Relative Employment (b) Relative Hours

Notes: The figure reports correlations between the cyclical component of relative employment/hours and the cyclical component of real GDP for each country. To compute trends, relative hours and relative employment (female/male) of individuals aged 20–64 and annual real GDP for the period 1998–2019 are HP filtered with smoothing parameter 6.25. See the Appendix for data sources and details. The countries analyzed in detail in Section 3 are highlighted in red.

pation (Albanesi and Şahin 2018, Coskun and Dalgic 2020) and within-family insurance, i.e., countercyclical adjustments of women's labor supply in response to job loss (or risk thereof) of their husbands (Doepke and Tertilt 2016). These factors give rise to substantial variation in the cyclical behavior of women's labor supply across countries, depending on factors such as the local industry composition of employment, marriage rates, and married women's labor force participation. Nevertheless, as Figure 3 shows in almost all cases the end result is a lower cyclicality of women's compared to men's labor supply.

Beyond correlations of relative labor supply and the cyclical component of GDP, we can analyze cyclical variation in women's and men's labor supply in more detail using the methodology of Doepke and Tertilt (2016). Their analysis distinguishes the total volatility of labor supply (the percentage standard deviation of the Hodrick-Prescott residual) from its cyclical volatility, which is the percentage standard deviation of the predicted value of the Hodrick-Prescott residual of labor supply on the Hodrick-Prescott residual of GDP per capita. The concept of cyclical volatility captures the part of total volatility that is related to the economic cycle, as opposed to other factors such as variation in cohort sizes.

Table 1: Volatility of Hours Worked, by Gender and Marital Status, 1998-2019

		All		Married		Single	
	Total	Women	Men	Women	Men	Women	Men
		Total Volatility					
United States	1.27	0.99	1.54	0.80	1.23	1.29	2.12
Canada	0.86	0.67	1.06	0.61	1.01	0.93	1.31
Germany	1.02	0.87	1.14	0.89	0.94	1.04	1.59
Netherlands	1.12	1.28	1.10	1.80	0.81	1.21	1.62
Spain	1.58	1.41	1.83	1.23	1.49	1.86	2.50
United Kingdom	0.74	0.76	0.82	0.65	0.60	1.07	1.27
		Cyclical Volatility					
United States	1.16	0.85	1.41	0.64	1.13	1.11	1.92
Canada	0.71	0.49	0.87	0.40	0.73	0.66	1.16
Germany	0.82	0.62	0.93	0.51	0.74	0.72	1.25
Netherlands	0.78	0.67	0.83	0.86	0.55	0.53	1.21
Spain	1.48	1.27	1.64	0.90	1.22	1.76	2.26
United Kingdom	0.51	0.34	0.62	0.13	0.35	0.54	1.01
		Hours Share					
United States		42.96	57.04	23.57	36.15	19.39	20.89
Canada		41.97	58.03	27.53	39.83	14.44	18.20
Germany		38.27	61.73	19.86	36.76	18.41	24.97
Netherlands		35.39	64.61	17.78	37.24	17.61	27.37
Spain		38.30	61.70	20.71	38.25	17.59	23.45
United Kingdom		39.12	60.88	19.80	35.56	19.33	25.31
		Volatility Share					
United States		31.14	68.86	12.87	34.69	18.33	34.11
Canada		29.04	70.96	15.47	41.24	13.42	29.87
Germany		29.45	70.55	12.41	33.36	16.16	38.07
Netherlands		30.58	69.42	19.52	26.05	12.04	42.38
Spain		32.49	67.51	12.44	31.36	20.71	35.49
United Kingdom		26.06	73.94	5.07	24.63	20.37	49.93

Notes: See Appendix B for data sources. Total volatility is the percentage standard deviation of the Hodrick-Prescott residual of average labor supply per person in each group. Cyclical volatility is the percentage deviation of the predicted value of a regression of the HP-residual on the HP-residual of GDP per capita. Hours share is the share of each component in total hours. Volatility share is share of each group in the cyclical volatility of total hours.

Table 1 shows how the total and cyclical volatility of labor supply for different groups compares between the United States and five other countries: Canada, Germany, the Netherlands, Spain, and the United Kingdom. In five of the six countries, volatility is smaller for women than for men. Only the Netherlands stand out with a higher volatility for women than men.[4] When focusing on cyclical volatility, in all countries (including the Netherlands) women's hours worked vary less over the business cycle than men's. The gender gap is sizeable, ranging from a modest difference in the Netherlands to a cyclical volatility that is almost twice as high for men relative to women in the United Kingdom.

With the exception of the Netherlands, the cyclical volatility of labor supply is lower for married women than for single women. Among singles, the cyclical volatility of single women is lower than that of single men in all countries. Thus, women's labor supply in general, and married women's in particular, tends to dampen fluctuations in aggregate labor supply over the business cycle. The overall impact of women on the behavior of aggregate labor supply not only depends on the volatility of women's labor supply, but also on their share in aggregate labor supply. Women's share of total hours varies from 35 percent in the Netherlands, where married women usually work part-time, to 43 percent in the United States. Women's contribution to the overall volatility of aggregate labor supply is always lower than the hours share and varies between 26 percent in the United Kingdom and 32 percent in Spain. Hence, in all countries women account for less than a third of the volatility of aggregate labor supply. The volatility share of married women differs widely across countries, ranging from only 5 percent in the United Kingdom to almost 20 percent in the Netherlands.

Figure A1 in the Appendix displays the cyclical component of hours worked over time for each country. An interesting observation that has not been explored yet in the literature is that the male cycle seems to lead the female cycle, especially for singles.

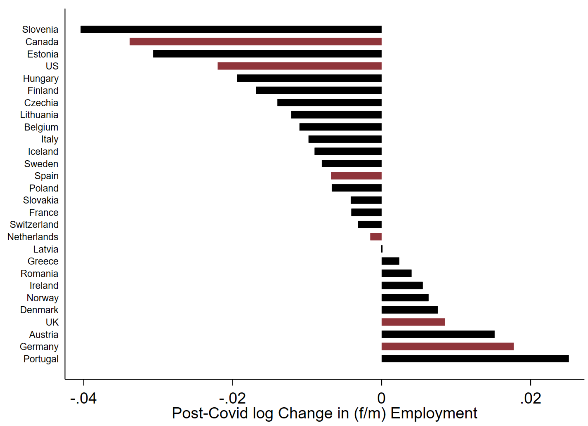
2.2 The Pandemic Recession

The evidence shown so far establishes that in pre-2020 economic fluctuations, women's labor supply was less cyclical than men's across a wide range of countries. Let us now consider what happened during the pandemic recession of 2020. Figure 4 shows how

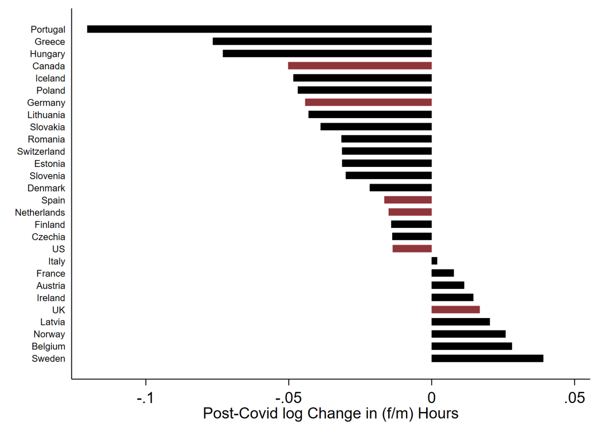
[4]The higher volatility for women in the Netherlands is related to a large decline in hours worked of married women in 2005, see Figure 1b. There was a break in the time series in 2005 which we attempted to correct but which may still have an impact on measured volatility.

the labor supply of women versus men changed in each country. Unlike in a regular recession, women's labor supply fell relative to men's in 18 of 28 countries when measured by employment, and in 19 of 28 countries when measured by hours worked. Quantitatively, we observe larger changes in terms of hours worked, with a drop of more than 10 percent in women's relative hours in Portugal.

Figure 4: Post-Covid Change in relative Female/Male Labor Supply



(a) Relative Employment



(b) Relative Hours

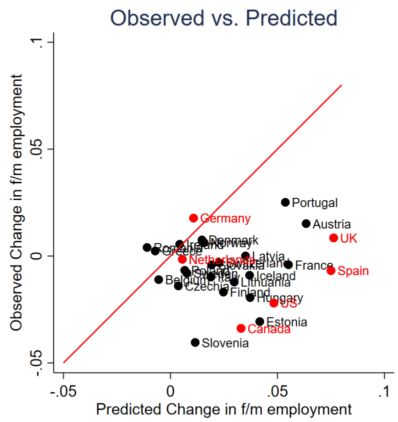
Notes: The figure reports the log change in seasonally adjusted relative employment (female/male) and a relative hour worked index (female/male) between 2019-Q4 and 2020-Q2. See Appendix C for further details and data sources.

Rather than looking at the absolute change in the ratio of women's to men's labor supply, we can also ask how observed changes compare to what would be expected based on the pre-pandemic relationship of women's and men's labor supply to the business cycle. Accordingly, Figure 5 plots the actual change in labor supply in each country against the predicted change based on pre-pandemic data. Here we see that most countries are below the 45-degree line, implying that women's relative labor supply either declined or increased by less than what would have been expected based on earlier recessions (the few exceptions are all close to the 45-degree line). The countries that display a decline in men's relative employment even during the Covid-19 recessions (most notably Portugal, Austria, and the United Kingdom) are countries that have particularly pronounced mancessions in regular times.

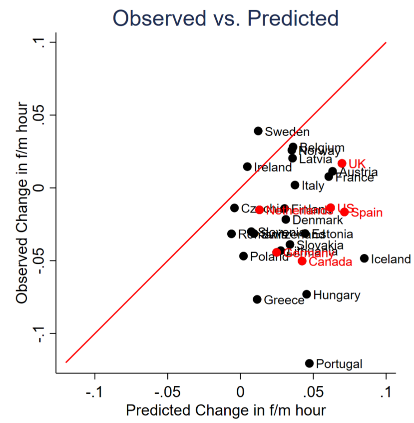
2.3 Pattern Across Industries

Why is the pandemic recession so different from usual recessions in its impact on women's versus men's employment, and what explains the substantial variation in the impact

Figure 5: Predicted versus Observed Changes in Women's Relative Labor Supply



(a) Relative Employment



(b) Relative Hours

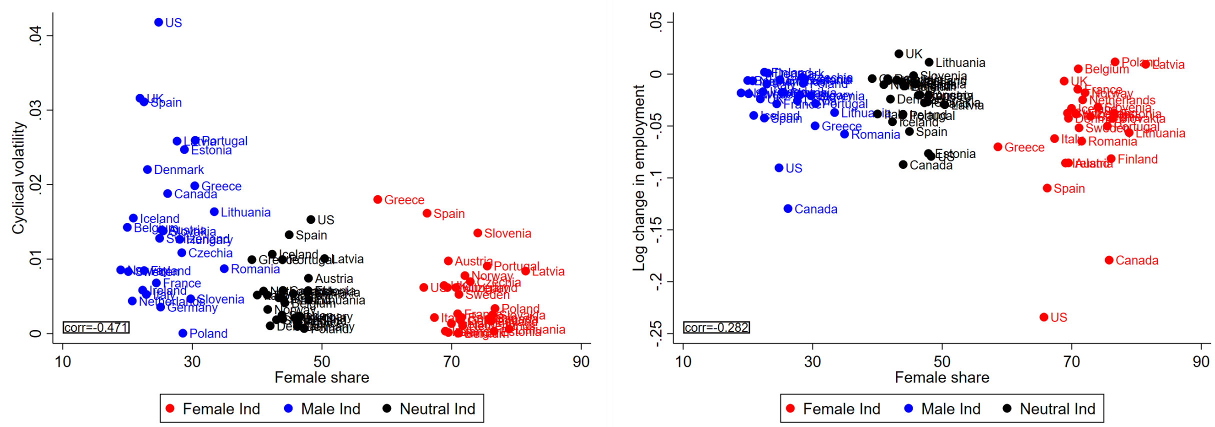
Notes: Observed changes are the ones reported in Figure 4. Predicted changes are calculated by multiplying the estimated coefficient from a regression of the cyclical component of relative employment/hours on the cyclical component of GDP (for the years 1998–2019) and the observed GDP change between 2019-Q4 and 2020-Q2.

across countries? Starting with Alon et al. (2020a), the literature has focused on two explanations for the gendered impact of a pandemic recession. The first explanation is about the impact of the recession on different industries and occupations; because the impact is related to lockdowns and social distancing measures, the parts of the economy most affected by the current downturn are not the ones that decline the most in regular recessions. Second, widespread school and daycare closures affect the ability of parents, and often mothers, to work.

We can use our cross-country data set to provide a first assessment of the first explanation, namely the role of the employment composition by industry. To do this, we divide industries into three groups: those with high male employment shares, those with high female employment shares, and "neutral" industries in the intermediate range. The industry classification is the same for all countries (see Appendix B.2 for details). We can now check how male, female, and neutral industries are affected by regular recessions and the pandemic recession in each country.

The left panel of Figure 6 shows that, as expected, in pre-2020 data male industries display more cyclical volatility in employment than female industries. At the same time, the figure also shows large cross-countries variation; for example, in the US the downward sloping pattern is particularly pronounced, while in Slovenia female industries are more volatile than male ones and in Germany there is little difference in the cyclical

Figure 6: Regular Recessions and the Pandemic Recession in Female versus Male Industries



(a) Cyclical Volatility across Industries

(b) The Pandemic Recession across Industries

Notes: Each dot depicts a group of industries (female, male, or neutral) in a country. See Appendix for data sources and details. Panel (b) reports log changes of seasonally adjusted aggregated industry employment between 2019Q4–2020Q2. Cyclical volatility is calculated for the period 2008–2019 (2010–2019 for Switzerland) at a quarterly frequency, and is defined as the log deviation of the predicted value of a regression of the HP-residual of industry employment on the HP-residual of real GDP. The female share for each industry is the average of 2019.

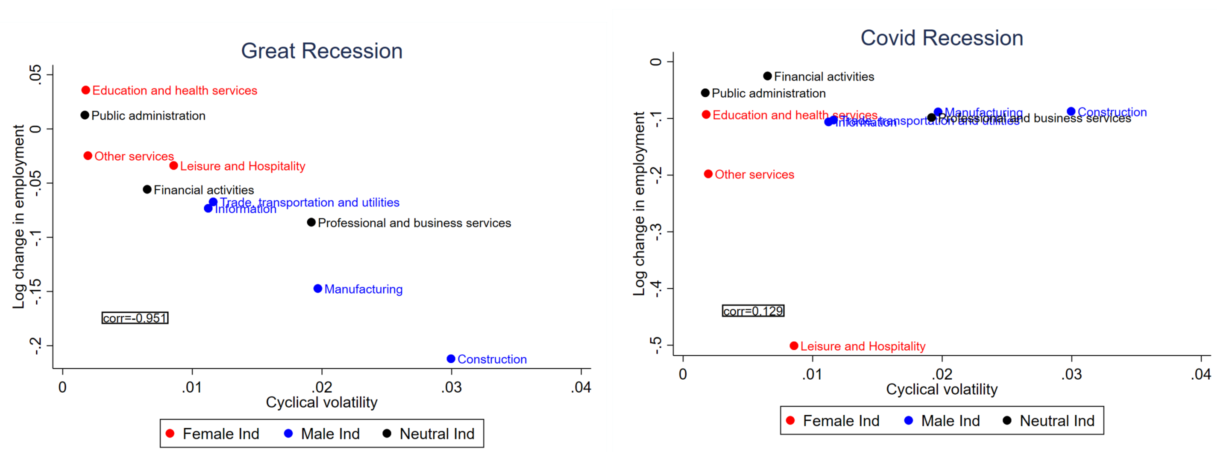
volatility between male and female industries.

The right panel shows how employment in the same set of industries in each country was affected by the pandemic recession in 2020. In a regular recession we would expect to observe an increasing slope moving from male to female industries, i.e., larger job losses during the recession in male industries. The actual pattern is the opposite: on average, female industries suffered larger employment losses than male industries. In Spain, for example, the employment decline was more than twice as large in female industries than male ones. Once again there is sizeable variation across countries. For example, in the United Kingdom employment declines were slightly smaller in female industries. Differences in industry composition together with the impact of the pandemic recession on industries with relatively more female or male workers can account for some of the variation evident in Figure 4. For example, women's employment was much strongly affected in Spain compared to the United Kingdom, and according to Figure 6b differences in the impact of the crisis across sectors (such as the large impact on and the large size of the tourism sector in Spain) can account for some of that.

Another way to see how starkly different the pandemic recession is from previous recessions is to compare it specifically to the Great Recession. In Figure 7 we do this for the

United States. The left panel shows that the most cyclical sectors, especially construction and manufacturing, also experienced the largest employment declines in the Great Recession. As the right panel shows, in the pandemic recession the pattern is completely different: the largest employment declines were experienced by the leisure sector, which is usually not particularly cyclical. It also happens to be a sector dominated by female employees.

Figure 7: Employment Decline across Sectors, United States



(a) Employment Decline in Great Recession

(b) Employment Decline in Pandemic Recession

Notes: Data from Bureau of Labor Statistics, seasonally adjusted quarterly industry employment numbers 1998-2020. Cyclical volatility has been calculated for the period 1998–2019, and is defined as the log deviation of the predicted value of a regression of the HP-residual of industry employment on the HP-residual of real GDP. Employment change in the Great Recession is the log change in industry employment from peak to through by NBER recession dates, and for the Covid recession the employment change corresponds to the period 2019Q4–2020Q2.

2.4 The Childcare Channel in Cross-Country Data

In addition to industry effects, increased childcare needs due to school and daycare closures are the other leading explanation for the impact of the recession on working women. The impact of this channel varies across countries, depending on factors such as mothers' labor force participation and the length and severity of school and daycare closures. For example, in Sweden school closures were much more limited than in most other countries, and Sweden is also one of the few countries were women's relative hours increased in the pandemic recession (see Figure 4b).

Childcare (or the lack thereof) likely matters not just for the gender gap in labor supply, but also for the overall employment impact of the pandemic. School closures affect all working parents, so that the extent of school closures should have an impact on the overall depth of the recession. In addition, the more hours women work in normal times, the more likely it is that reductions in work hours are necessary to cope with the increased childcare needs during the pandemic.

Table 2: Correlates of Change in Aggregate Hours Worked during the Pandemic Recession across Countries

	(1) Hour Change	(2) Hour Change	(3) Hour Change	(4) Hour Change	(5) Hour Change
School Closure Index	-0.207***	-0.157**			-0.085
	(0.007)	(0.033)			(0.241)
Pre-Pandemic Female Hours		0.011**			
		(0.043)			
Share of Hospitality			-1.852***		-1.943***
			(0.001)		(0.000)
Teleworkable fraction				0.642**	0.579**
				(0.034)	(0.041)
N	28	28	28	27	27
R2	0.251	0.366	0.362	0.168	0.630

Notes: p-values in parentheses. p<0.1, ** p<0.05, *** p<0.01. See Appendix B.2 for data sources.*

To explore the overall impact of these channels on the labor market during the pandemic recession, in Tables 2 to 5 we present cross-country regression results that show how various country-level characteristics are correlated with the aggregate changes in the labor market and with relative changes for women compared to men. With regard to aggregate employment, in column (1) of Table 2 we regress the overall change in labor supply during the crisis (the hours index) in each country on an index that measures the severity of school closures. The regression shows that indeed, countries with more severe school closures experienced a greater drop in labor supply; the school closure index alone accounts for about 25 percent of the variation in hours changes. However, on its own the school closures index is not associated with larger employment changes or with differential impacts on women versus men (column (1) in Tables 3–5).[5]

In interpreting these results, it should be kept in mind that they represent correlations in cross-country data that are not necessarily causal and that are subject to the usual

[5]The severity of school closures may also be endogenous to the labor market structure. For example, in countries where many employees have children, political pressure may have kept more schools open. Indeed, Figure A3 in the Appendix shows that in countries where women work more and/or a greater share of labor force is in need of childcare, schools closures were less severe.

Table 3: Correlates of Change in Aggregate Employment during the Pandemic Recession across Countries

	(1) Emp Change	(2) Emp Change	(3) Emp Change	(4) Emp Change	(5) Emp Change
School Closure Index	-0.001	-0.006			0.046*
	(0.970)	(0.843)			(0.080)
Pre-Pandemic Female Hours		-0.001			
		(0.624)			
Share of Hospitality			-0.479**		-0.474***
			(0.016)		(0.003)
Teleworkable fraction				-0.026	0.121
				(0.764)	(0.216)
N	28	28	28	27	27
R2	0.000	0.010	0.203	0.004	0.357

Notes: p-values in parentheses. p<0.1, ** p<0.05, *** p<0.01. See Appendix B.2 for data sources.*

Table 4: Correlates of Change in Relative Hours Worked (Women/Men) during the Pandemic Recession across Countries

	(1) Hour(f/m) Change	(2) Hour(f/m) Change	(3) Hour(f/m) Change	(4) Hour(f/m) Change	(5) Hour(f/m) Change
School Closure Index	-0.030	-0.049			0.059
	(0.392)	(0.182)			(0.181)
Pre-Pandemic Female Hours		-0.004			
		(0.125)			
Share of Hospitality			-0.110		-0.250
			(0.676)		(0.307)
Teleworkable fraction				0.313**	0.474***
				(0.016)	(0.007)
N	28	28	28	27	27
R2	0.028	0.117	0.007	0.212	0.290

Notes: p-values in parentheses. p<0.1, ** p<0.05, *** p<0.01. See Appendix B.2 for data sources.*

Table 5: Correlates of Change in Relative Employment (Women/Men) during the Pandemic Recession across Countries

	(1) Emp (f/m) Change	(2) Emp (f/m) Change	(3) Emp (f/m) Change	(4) Emp (f/m) Change	(5) Emp (f/m) Change
School Closure Index	-0.004	-0.013			-0.005
	(0.800)	(0.382)			(0.806)
Pre-Pandemic Female Hours		-0.002*			
		(0.067)			
Share of Hospitality			0.029		0.062
			(0.795)		(0.587)
Teleworkable fraction				-0.025	-0.041
				(0.648)	(0.587)
N	28	28	28	27	27
R2	0.003	0.130	0.003	0.008	0.022

Notes: p-values in parentheses. p<0.1, ** p<0.05, *** p<0.01. See Appendix B.2 for data sources.*

limitations of cross-country regressions. For example, differences in the severity of the pandemic across countries would be expected to generate some variation in the severity of school closures and also have a direct impact on employment (e.g. through the length of lockdowns). Hence, the results described in Tables 2–5 should be interpreted as correlations that help summarize the data and can provide a first pass at assessing the importance of different channels, without being conclusive on their own.

The next variable we explore is the pre-pandemic level of women's labor supply. In a country were most mothers work full time, increased childcare needs during the pandemic may have a larger impact compared to a country were many mothers are either out of the labor force or working part time. Our results indicate that, when also controlling for the school closures index, countries where women's labor supply is higher experienced somewhat smaller aggregate declines in hours (column (2) of Table 2), but larger relative employment declines for women compared to men (column (2) of Table 5).

Next, we consider the role of industry composition and job characteristics. In the pandemic recession, the hospitality sector (including restaurants) has seen the largest employment decline across countries (see the right panel of Figure 7 for the United States).[6] The size of the hospitality sector also varies widely across countries (in our sample, from 5.6 percent of total employment in Poland to 16 percent in Spain). Column (3) of Tables 2 and 3 shows that a larger hospitality sector is indeed associated with a substantially

[6] In these regressions we use a broad definition of hospitality that includes hospitality, leisure, and other services.

larger overall decline in hours and employment in a country. However, there is no discernible impact on the relative changes for women versus men (column (3) of Tables 4 and 5).

In terms of job characteristics, arguably the most important one during the pandemic is whether the job can be done from home during shutdowns. Indeed, we find that countries with a larger share of telecommutable jobs experience a smaller decline in labor supply during the pandemic (column (4) of Table 2) and a smaller impact on the labor supply of women compared to men (column (4) of Table 4). When we include both measures together with the school closures index, both continue to have a substantial impact on the total hour change (column (5) in Table 2), whereas the effect of school closures turns insignificant. This regression also has the highest R^2 among specifications considered, accounting for more than 50 percent of the variance in overall labor supply changes across countries.

We also considered a number of other potential determinants of the labor market impact of the pandemic, but found that they showed little correlation with employment changes and gender differences.[7] An additional conjecture is that the extent of employment protection may explain some of the variation in employment losses across countries. We indeed find that the OECD index of employment protection for temporary workers has a small correlation with overall employment changes in the expected direction, but the effect is quantitatively small and accounts for little of the observed variance across countries. Employment protection does not have a significant effect on gender differences in the impact of the pandemic.

While the correlations documented in Tables 2-5 are suggestive, only so much can be learned from cross-country correlations in aggregate data. To make progress, we now turn to household-level evidence from a smaller set of countries.

3 Micro Data Across Countries

The potential explanations for the gendered impact of the current pandemic recession generate distinct implications for which groups of women would suffer the biggest employment losses. For example, if childcare obligations during school closures were the main driving force behind women's employment losses, we would expect to observe a

[7] These include the existence of emergency care, the duration of short-term work allowances, a government response stringency index, and the fraction of employees with childcare obligations.

large impact on the employment of mothers with young children, but not on women without children or women with adult children. We can use micro data from national employment surveys to examine these implications. For this analysis, we focus on a smaller set of countries for which this data is already available up to at least the second quarter of 2020, namely the United States, Canada, Germany, the Netherlands, Spain, and the United Kingdom. As Table 6 shows, these countries also display a lot of variation in terms of the structure of women's labor supply, industry composition, and the policy response to the pandemic, which will provide further evidence on the additional driving forces discussed in the previous section.

Table 6: Policies and Labor Market Structure Across Six Countries

Country	School Closure Index	Teleworkable jobs	Average female hours	Share of hospitality, leisure, other services	Emp protection temp worker	Emp protection regular worker	Pre-Covid Cyclicality of Relative Hours
Canada	0.88		23.04	0.11	0.28	1.68	-0.60
Germany	0.64	0.37	22.40	0.08	1.92	2.33	-0.69
Netherlands	0.51	0.42	20.45	0.09	1.48	2.88	-0.21
Spain	0.76	0.32	20.30	0.16	3.10	2.43	-0.37
UK	0.78	0.44	23.23	0.11	0.54	1.90	-0.43
US	0.50	0.42	25.04	0.15	0.33	1.31	-0.76

Notes: See Appendix B.2 for data sources.

3.1 Data and Empirical Design

The data stem from a variety of surveys (see Appendix C for details on the data sources and the sample used) and there is variation in the questionnaires, the frequency of the surveys, and sample selection. We start by focusing on regressions that can be carried out in a similar way in all countries and give us a set of comparable results. The first set of regressions aims to examine the two leading explanations for the large impact of the pandemic on women's employment, namely the role of childcare and the role of industry and occupation. Our benchmark regression equation takes the form:

$$y_{it} = \beta_0 + \beta_1\,\mathrm{F}_i + \beta_2\,\mathrm{D}_t + \beta_3\,\mathrm{F}_i \times \mathrm{D}_t + \boldsymbol{\beta}_4\,\mathbf{X}_{it} + \epsilon_{it}. \tag{1}$$

Here y_{it} is the outcome variable of interest for individual i at time t, which is either a binary employment indicator or the inverse-hyperbolic sine transform of hours worked last week. We apply this transformation to approximate the natural logarithm of hours worked last week while keeping the extensive margin of employment (i.e. zero hours).[8]

[8]See Bellemare and Wichman (2020) for more discussion and applications of the inverse hyperbolic-sine transformation.

F_i is an indicator for female, and D_t is an indicator for the Covid-19 pandemic, here corresponding to the second and third quarters of 2020 (the last two quarters in our data sets). The vector $\mathbf{X}_{it}$ consists of control variables that include gender specific time trends in labor supply, quarterly seasonal dummies, age dummies, education categories, marital status, and race.[9] We also include a dummy for education workers in the summer months, since hours worked for this group drop strongly in the summer months. The main coefficient of interest is β_3 on the interaction of F_i and D_t. Here 100*β_3 captures the percentage difference in the impact of the pandemic on women versus men.[10]

We use additional regressions to characterize the extent to which the raw gender differences are due to industry, occupation, and childcare responsibilities. To get at the role of industry and occupation, we employ the following specification:

$$y_{it} = \gamma_0 + \gamma_1 \, \mathrm{F}_i + \gamma_2 \, \mathrm{D}_t + \gamma_3 \, \mathrm{F}_i \times \mathrm{D}_t + \boldsymbol{\gamma}_4 \, \mathbf{Job}_{it} + \boldsymbol{\gamma}_5 \, \mathbf{Job}_{it} \times \mathrm{D}_t + \boldsymbol{\gamma}_6 \, \mathbf{X}_{it} + \epsilon_{it}. \tag{2}$$

Here $\mathbf{Job}_{it}$ is a vector combining occupation and industry information, with a dummy variable for each occupation-industry combination and an additional dummy variable for those not working to keep them in the sample. This job-type variable is interacted with the pandemic dummy D_t, which captures the differential impact of the recession on workers in different industries and occupations. The coefficient 100*γ_3 captures percentage changes in the gender gap net of any industry-by-occupation-specific pandemic effects. For example, if gender differences arose entirely because more women than men work in the hospitality sector, we would expect to see a negative estimate of β_3 in Regression (1) but a zero estimate of γ_3 in Regression (2).

Our third main specification examines the role of childcare responsibilities for gender gaps in employment during the pandemic by focusing on differences between individuals with and without children. The specification has the following form:

$$y_{it} = \boldsymbol{\delta}_0 \, \mathbf{Kid}_{it} + \boldsymbol{\delta}_1 \, \mathrm{F}_i \times \mathbf{Kid}_{it} + \boldsymbol{\delta}_2 \, \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\delta}_3 \, \mathrm{F}_i \times \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\delta}_4 \, \mathbf{X}_{it} + \epsilon_{it}. \tag{3}$$

[9] For Germany, the Netherlands, Canada, and Spain we use migration status instead of race, see Appendix C for details.

[10] Throughout our micro data analysis we use this difference in the percentage point change to measure the gendered impact of the pandemic. An alternative measure would be the difference in the percent changes, which generally should lead to larger gender gaps as women's employment rates were lower than men's prior to the pandemic. Thus we see our estimates as a lower bound of the gendered impact of the pandemic. See Bluedorn et al. (2021) for a useful comparison of the two measures in cross-country data.

Here $\mathbf{Kid}_{it}$ is a vector of three dummy variables grouping households by age of their youngest child into three groups: pre-K (<5), school age (5-17), and a third group that combines those with no or only adult children.[11] The coefficients $\boldsymbol{\delta}_0$ to $\boldsymbol{\delta}_3$ are vectors in this regression with a separate entry corresponding to each child group. In this regression, the coefficients in $\boldsymbol{\delta}_3$ capture the gender gap in the employment impact of the pandemic conditional on the child group. If gender differences arose solely because mothers are more affected by the rise in childcare needs during the pandemic than fathers, we would expect a negative coefficient within the groups with young and school-age children, but a zero coefficient in the no child/adult child group.

Our final specification combines (2) and (3) by adding the work-type controls and interactions to the child-type regressions:

$$y_{it} = \boldsymbol{\theta}_0\,\mathbf{Kid}_{it} + \boldsymbol{\theta}_1\,\mathrm{F}_i \times \mathbf{Kid}_{it} + \boldsymbol{\theta}_2\,\mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\theta}_3\,\mathrm{F}_i \times \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\theta}_4\,\mathbf{Job}_{it} + \boldsymbol{\theta}_5\,\mathbf{Job}_{it} \times \mathrm{D}_t + \boldsymbol{\theta}_6\,\mathbf{X}_{it} + \epsilon_{it}. \quad (4)$$

Once again, adding work type controls allows us to assess how much of the observed effects are due to industry and occupation. For example, one may conjecture that young mothers have different jobs than young fathers; the full specification allows us to measure the differential impact of the pandemic on the employment of mothers and fathers beyond what is accounted for by such industry and occupation differences.

3.2 Gender Gaps Across Countries in the Micro Data

Table 7 summarizes the results for these regressions with employment status (employed or not) as the left-hand side variable, and Table 8 does the same for hours. For comparison, the first row displays the overall percentage employment change (Table 7) and hours change (Table 8) in each country during the pandemic. Employment dropped by more than five percent in the United States, Canada, and Spain, by less than one percent in Germany and the United Kingdom. Changes in hours are much larger and range from a decline of 36 percent in the United States to more than 50 percent in Germany.[12]

[11] In Spain, the group of school-age children includes children up to the age of 19, based on the available age brackets in the Spanish micro data set. Similar data limitations in Germany allow us to only form two groups of households in Germany: those with a child below 16 and those without.

[12] The large impact on hours worked in Germany arises in part because the work-time measure here includes commuting time, which drops while many people work from home during the pandemic. In addition, in the German data, post-pandemic hours are observed primarily in Q2/2020, potentially leading to larger effects compared to other countries that rely on hours observed all the way through September

Table 7: Pandemic-induced Change in Employment and in the Gender Gap in Employment: Regression Coefficients from Individual Country Regressions

	USA	CAN	DEU	NLD	ESP	GBR
Overall employment decline	-6.34	-5.52	-0.28	0.67	-6.96	-0.13
	(0.00)	(0.00)	(0.55)	(0.13)	(0.00)	(0.59)
Basic gender gap (β_3)	-1.91	-0.44	-1.34	1.51	-1.01	0.15
	(0.00)	(0.13)	(0.13)	(0.21)	(0.09)	(0.81)
pre-K kids ($\delta_{3,\text{pre-K}}$)	0.13	2.65		1.13	0.20	1.38
	(0.83)	(0.00)		(0.59)	(0.84)	(0.16)
school age kids ($\delta_{3,\text{school}}$)	-4.23	-1.76	-1.12	0.92	-1.97	-0.80
	(0.00)	(0.00)	(0.43)	(0.55)	(0.01)	(0.30)
no kids ($\delta_{3,\text{none}}$)	-1.57	-1.05	-1.04	2.06	-1.13	-0.47
	(0.00)	(0.00)	(0.33)	(0.13)	(0.12)	(0.52)
w/ industry & occ controls (γ_3)	-1.09	-0.46	-1.32	1.11	0.04	-0.34
	(0.00)	(0.02)	(0.16)	(0.28)	(0.41)	(0.52)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-0.81	0.14		1.05	0.08	0.12
	(0.03)	(0.63)		(0.56)	(0.15)	(0.89)
school age kids ($\theta_{3,\text{school}}$)	-1.79	-1.63	-0.99	0.31	-0.05	-0.74
	(0.00)	(0.00)	(0.50)	(0.81)	(0.41)	(0.26)
no kids ($\theta_{3,\text{none}}$)	-0.95	-0.33	-1.20	1.52	0.08	-0.69
	(0.00)	(0.15)	(0.28)	(0.18)	(0.15)	(0.25)

Notes: Coefficients reported are in percentage points. Sample includes all civilians aged 25 to 55 who are either employed, unemployed or not in the labor force. The p-values are reported in parentheses below estimates. Unless otherwise noted, all regressions include gender specific time trends and controls for age, education, race, and marital status, in addition to quarterly indicators and a fixed effect for education sector workers in summer months to control for seasonality. No controls are used in the estimation of the overall employment decline. For Canada, Germany, the Netherlands, and Spain, we group people by migration background instead of race. Child age brackets are assigned by the age of the youngest child (<5 and 5-17). In Spain, the group of school-age children includes those up to the age of 19. Due to data limitations, for Germany we can only estimate the combined effect of having children below 16 (including pre-K), which in the table is reported in the "school age kids" rows. Furthermore, due to a shorter data availability, in Germany and the Netherlands we cannot control for gender specific time trends, quarterly indicators, and the summer-education fixed effect. For details on the data, see Appendix C.

The Netherlands are an outlier in both dimensions: the data actually indicate a small but insignificant rise in employment and hours during the crisis. Rather than reflecting a true increase in employment, it is more likely that this increase reflects a change in the questionnaire in the Dutch LISS survey that reduces comparability of reported hours before and during the pandemic.[13] We keep the Netherlands in the sample because the variation in outcomes across different groups in the crisis is still informative.

It is notable that Germany and the United Kingdom display the smallest decline in employment but among the largest drops in hours. This suggests an important role of furlough schemes in these countries that preserved employment while allowing large reductions in hours (often to zero), which should be kept in mind when interpreting the results.

The other entries in Tables 7 and 8 are estimates for the gender-gap coefficients of interest β_3, γ_3, $\boldsymbol{\delta}_3$, and $\boldsymbol{\theta}_3$. Each entry in the table corresponds to an estimate from a separate regression, and p-values are displayed in parentheses. The row labeled as "Basic Gender Gap" displays the coefficient estimate for β_3 for each outcome and for each country. In terms of employment, a sizeable and statistically significant gender gap in the impact of the pandemic on employment is observed only in the United States and to a smaller extent in Spain.[14] Note that according to Table 6, these two countries have the highest employment share of the hospitality sector. In terms of hours (Table 8), we observe a substantially larger impact on women's compared to men's labor supply in the United States, Canada, and Germany, but no statistically significant difference in the Netherlands, Spain, and the United Kingdom.[15] One reason for these cross-country differences is likely the different labor market structure in these countries. The fall in relative hours was large and significant in those countries where the pre-covid cyclicality of relative hours was high and where female hours worked are relatively high (see Table 6).

2020. Finally, for Germany we have only one pre-Covid data point on hours dating back to 2018. See Appendix C.3 for details on the German data.

[13] See Appendix C.4 for details.

[14] To reconcile the results in Tables 7 and 8 with Figure 4, note that the regression include various controls such as time trends and seasonal dummies, implying that results are not directly comparable. In addition, Figure 4 displays changes between Q4/2019 and Q2/2020 whereas the results in the current section are based on a longer time horizon. In those cases where coefficients are significant, the sign of effect does line up with Figure 4.

[15] Note that our measure of hours worked for Germany includes commuting time. Since men on average spend more time commuting than women, they also likely faced larger reductions in commuting time during the pandemic. Thus, the true increase in the gender gap in hours worked (without commuting) should likely be even larger than our estimate.

Table 8: Pandemic-induced Change in Hours and in the Gender Gap in Hours: Regression Coefficients from Individual Country Regressions

	USA	CAN	DEU	NLD	ESP	GBR
Overall hours decline	-36.17	-43.77	-52.18	6.91	-43.99	-42.20
	(0.00)	(0.00)	(0.00)	(0.14)	(0.00)	(0.00)
Basic gender gap (β_3)	-7.76	-6.50	-26.39	-6.63	-2.08	4.97
	(0.00)	(0.00)	(0.01)	(0.46)	(0.46)	(0.12)
pre-K kids ($\delta_{3,\text{pre-K}}$)	2.42	6.00		-67.85	11.02	13.80
	(0.40)	(0.01)		(0.01)	(0.03)	(0.01)
school age kids ($\delta_{3,\text{school}}$)	-17.86	-11.08	-16.23	-9.25	-4.60	-4.05
	(0.00)	(0.00)	(0.29)	(0.55)	(0.20)	(0.34)
no kids ($\delta_{3,\text{none}}$)	-6.63	-7.92	-31.25	5.89	-5.11	2.55
	(0.00)	(0.00)	(0.01)	(0.63)	(0.13)	(0.52)
w/ industry & occ controls (γ_3)	-5.20	-7.21	-22.38	-11.21	-2.16	0.53
	(0.00)	(0.00)	(0.03)	(0.22)	(0.24)	(0.87)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-3.66	-5.58		-65.79	0.43	7.06
	(0.08)	(0.00)		(0.01)	(0.91)	(0.16)
school age kids ($\theta_{3,\text{school}}$)	-8.94	-11.55	-10.17	-7.66	-4.93	-6.31
	(0.00)	(0.00)	(0.52)	(0.61)	(0.05)	(0.12)
no kids ($\theta_{3,\text{none}}$)	-4.19	-4.64	-29.71	-4.05	-1.23	-1.50
	(0.00)	(0.00)	(0.02)	(0.72)	(0.57)	(0.68)

Notes: Coefficients reported are log points difference of the pandemic's effect on women versus men. Hours index is calculated using inverse hyperbolic sine transformation of reported hours worked last week. Sample includes all civilians aged 25 to 55 who are either employed, unemployed or not in the labor force. The p-values are reported in parentheses below estimates. Unless otherwise noted, all regressions include gender specific time trends and controls for age, education, race, and marital status, in addition to quarterly indicators and a fixed effect for education sector workers in summer months to control for seasonality. No controls are used in the estimation of the overall hours decline. For Canada, Germany, the Netherlands, and Spain, we group people by migration background instead of race. Child age brackets are assigned by the age of the youngest child (<5 and 5-17). In Spain, the group of school-age children includes those up to the age of 19. Due to data limitations, for Germany we can only estimate the combined effect of having children below 16 (including pre-K), which in the table is reported in the "school age kids" rows. Furthermore, due to a shorter data availability, in Germany and the Netherlands we cannot control for gender specific time trends, quarterly indicators, and the summer-education fixed effect. For details on the data, see Appendix C.

The following rows of Tables 7 and 8 break down the gender gap between individuals with young children, school-age children, and either no or older children. Controlling for children matters a lot, in part because of differences within the two groups with children. In most cases, the gender gap in the "no kids" group is similar to the basic gender gap. With the exception of the Netherlands, among individuals with pre-K kids there is either no gender gap or women experience smaller employment and hours losses than men in this group. It is among workers with school-age children where large gender gaps in the impact of the crisis arise.

In the United States, for example, there is no significant gender gap among parents of pre-K kids for both employment and hours, a gender gap of 1.6 percentage points for employment and 6.6 percentage points for hours within the no-child group, but large gaps of 4.2 and 17.9 percentage points for employment and hours within the group with school-age children. The patterns in Canada, Spain, and the United Kingdom are qualitatively similar to the United States; while the magnitudes differ, in each case the gender gap is largest among parents of school-age children with the exception of the gender gap in hours in Spain where it equals the one of non-parents (in Germany, we do not have information to distinguish parents of pre-K and school-age children). The only country with a substantially larger impact on the labor supply of women in the pre-K group is the Netherlands, and even here the effect is only observed in terms of hours but not employment. Overall, these findings are consistent with a major role of school closures for explaining gender gaps during the pandemic.

3.3 The Role of Industry and Occupation

We next turn to the role of differential trends across industries and occupations during the pandemic. The bottom half of Tables 7 and 8 shows results after adding work-type controls for all industry-occupation combinations. As shown in Equation (2), these work-type controls are interacted with the pandemic dummy, so that we account for the differential impact of the pandemic on workers in each industry-occupation combination. If gender differences in a given group were entirely due to a different distribution of women and men in the group across industries and occupations, we would expect to observe a zero coefficient in the regressions controlling for these trends.

The results indicate that industry and occupation effects do matter, but only account for a limited fraction of gender gaps. Consider first the United States. After controlling for work type, the overall gender gap declines by 43 percent in terms of employment and

33 percent in terms of hours. Among parents of school-age kids, the gender gap declines by more than 50 percent in terms of employment and a little under 50 percent in terms of hours. While this shows that the work-type distribution accounts for a sizeable fraction of the gender gap among parents of school age children, this group still exhibits the largest gender gaps after controlling for work type. Another notable finding is that the gender gap among parents of pre-K kids switches sign; once work type is controlled for, mothers in this group lose more employment and hours than fathers. In other words, mothers of young children are likely to hold jobs that were relatively secure during the pandemic recession. However, even after controlling work type effects, the gender gap in this group continues to be smaller compared both to parents of older children and individuals without children.

There is a lot of variation in the role of work type across countries. In Canada, for example, gender differences among parents with pre-K children in terms of hours actually increase after controlling for work type, suggesting that fathers of young children work in jobs that were more exposed to the pandemic recession. The gender gap continues to be largest among parents of school-age children, while it shrinks for those without kids. In Germany, controlling for work type has only a small effect on the results. In Spain, controlling for work type accentuates the role of children for gender differences: a large and significant gender gap in terms of hours is only observed among parents of school-age children after including work-type controls. The pattern in the United Kingdom is similar but is just below statistical significance.

3.4 Interpreting the Empirical Findings

A few broader conclusions arise from the empirical analysis so far. First, in the Netherlands, Spain, and the United Kingdom gender gaps in the impact of the pandemic are generally small, and statistically insignificant for both employment and hours once work type is controlled for. Nevertheless, within this group we find a statistically significant gender gap in the hours response among parents of school-age children in Spain and parents of pre-K children in the Netherlands. In the Netherlands this gap in hours is quantitatively large, even though there is no gender gap in employment among the same parents. Evidently, many mothers of young children in the Netherlands reduced their hours at work while holding on to their job. The ability to do so depends on the availability of flexible furlough schemes and/or additional parental leave, which is one way in which policy choices shape the gender gap in the labor market during the crisis.

The remaining countries of the United States, Canada, and Germany all display a substantial overall gender gap in the hours response to the pandemic, with or without work-type controls. In the United States and Canada we also observe gender gaps in the employment impact of the crisis, whereas there are no statistically significant employment effects in Germany. In fact, in Germany there is no statistically significant decrease in overall employment (both men and women), even though the decline in hours is large, once again suggesting that employment protection and furlough schemes—which are extensive in Germany ("Kurzarbeit"), see Table 6—play an important role in shaping the employment effects of the recession.

Moving on to the role of childcare, in both the United States and Canada we find that the gender gap in the impact of the pandemic on employment and hours is largest among the parents of school-age children, and smallest (and even reversed in sign) among the parents of pre-K children under the age of 5. While the large gender gap among parents of school-age children lines up with a notion from the existing literature that childcare responsibilities during school and daycare closures have a negative effect on mothers' employment, our findings for the parents of younger children do not support this channel and are surprising at first sight. In terms of the sign of the effect on parents of young children, it turns out that controlling for industry and occupation is crucial: without such controls mothers experience smaller employment and hours losses than fathers in this group, but mothers' losses are larger after allowing for different trends across work types. In other words, among parents of young children, mothers who are in the labor force are more likely than fathers to work in industries and occupations that were relatively protected from the effects of the pandemic.

Still, even after introducing work type controls, the gender gap is substantially smaller among parents of young children compared to parents of school-age children. We conjecture that this observation may reflect a selection effect. The labor force participation of mothers of young children is lower than that of mothers of school-age children. Mothers who decide to work while raising a young child may have stronger labor force attachment than average women. Also, the fact that a mother of a younger child is working may reflect that she has more help with childcare, be it through a father who does a large share of the work, the presence of other family members such as grandparents who help out, or the financial means to employ a nanny. The same factors may also lead to a smaller impact of the pandemic recession on these women's employment. Mothers of young children who managed to work prior to the pandemic without using formal childcare clearly experienced less of a shock to their childcare needs compared to mothers of older children who normally attend school.

A final notable outcome is that even after allowing for the childcare and industry and occupation channels, sizeable gender gaps remain. The last rows of Tables 7 and 8 show that within the no-child group and after controlling for work type effects, women suffer larger employment losses than men in the United States, and larger reductions in hours of labor supply in the United States, Canada, and Germany. In fact, the gender gap within the no-child group is only slightly smaller than the overall gender gap in the United States and Canada, and larger (in terms of hours) in Germany. This shows that the gender gap in the impact of the pandemic goes well beyond the childcare and industry/occupation channels that have been emphasized by the literature so far. Understanding this pervasive nature of the gender gap in the impact of the pandemic, which constitutes a sharp difference from previous recessions, is an important challenge for future research.

3.5 Relating the Findings to the Literature

Several studies have analyzed gender differences in the labor market during the pandemic, typically focusing on one country at a time. None of these studies has applied the same methodology to analyze multiple countries in a comparable way. Existing studies also analyze only a subset of the issues that we do, and often only with data from the first couple of months of the pandemic. Still, to the extent that the scope of existing studies overlaps with ours, it is instructive to check how the results line up.

A number of studies have been conducted about the United States, most of them using CPS data as we do. Some of the early studies include data only until April or May 2020 and each of them looks only at a subset of the issues we do. Nevertheless, by and large the results support our findings of large gender gaps in employment and hours reductions in response to the pandemic, especially for those with children (Dias, Chance, and Buchanan 2020; Cowan 2020; Montenovo et al. 2020; Fabrizio, Gomes, and Tavares 2021; Collins et al. 2020; Couch, Fairlie, and Xu 2020). There are two papers that exploit geographic variation in school and daycare closures to isolate the effect of increased childcare needs. Heggeness (2020) studies school closures and finds that mothers living in early closure states were more likely to take temporary leave or stop working entirely. Even mothers who maintained their jobs in early closure states were 53 percent more likely to not be at work compared to mothers in late closure states. Russell and

Sun (2020) analyze childcare center closures instead and find similar effects for mothers of younger children. Using a triple-differences approach, they find evidence that the unemployment rate of mothers of young children increased substantially.

Like we do, studies analyzing Canadian data find sizeable gender gaps in labor supply declines. Qian and Fuller (2020) analyze the Canadian LFS (same data as we use) and find a large increase in the gender employment gap for parents of primary school age (6-12) children. They find even larger gender gaps when "being employed and at work" is used as an outcome variable. Lemieux et al. (2020) document that employment and hours worked of mothers with school-age children dropped substantially early on in the pandemic. Beauregard et al. (2020) analyze data from Quebec and find a larger impact of the pandemic on mothers relative to fathers in dual-parent households. They also find larger employment declines for single parents compared to dual-parent households. They further exploit the differential timing of primary school re-openings across regions. Using a triple-difference-strategy, they find a positive effect of re-openings on parental work, a more pronounced effect on single mothers, and stronger impact when the job cannot be done from home.

For the United Kingdom, like we do, Hupkau and Petrongolo (2020) find no increase in the gender gap in paid employment using the same labor force survey that we rely on. One explanation for these findings may be a more equal division of childcare within British households. Hupkau and Petrongolo (2020) and Sevilla and Smith (2020) both document a decline in the gender childcare gap during the pandemic, especially when men can work from home or lost their jobs. Within specific subgroups, some studies do find gender gaps even in the United Kingdom. Andrew et al. (2020a) focus on two-parent families and find larger declines in employment for mothers than fathers within this group. Analyzing data from a real time survey in April, Adams-Prassl et al. (2020b) also find gender gaps in employment losses in the United Kingdom. Adams-Prassl et al. (2020a) document a different kind of gender gap in furlough decisions: mothers were more likely than fathers to initiate furloughing (as opposed to it being the employer's decision), while no such gender gaps were found among childless workers.

For the Netherlands, Holler et al. (2021) use the same data that we employ and find little overall widening of the gender gap in employment or hours, in line with our findings. They distinguish essential from non-essential workers and find that women working in non-essential occupations reduced hours by more than men in the same occupations, but the opposite pattern is observed in essential occupations, where women reduced hours by less. Meekes, Hassink, and Kalb (2020) use administrative data for the Netherlands until June 2020. Like us, they find no significant widening of the gender employment gap in the first half of 2020. They argue that this is largely due to institutions such as a large short-time work scheme, generous paid family leave, and the availability of emergency childcare. The authors do find gender differences among subgroups: single moms of small children classified as essential workers experienced larger reductions in hours worked than other female essential workers.

González (2021) uses the Spanish labor force survey up until the third quarter and, in contrast to us, finds no evidence for a gender gap in employment losses. However, the paper uses a different definition of employment (classifying those furloughed and working zero hours as unemployed, while we define furloughed workers as employed) and does not consider hours worked, which likely explains the different result.

Previous findings for Germany are mixed. Adams-Prassl et al. (2020b) find no significant gender gap in employment losses in data from a real time survey conducted in April 2020. Möhring, Reifenscheid, and Weiland (2021) find that women participate less in short-time work in Germany, so that women's employment is more polarized between job loss or working on-site. Dullien and Kohlrauch (2021) argue that school closures played a relatively small role for aggregate employment and hours losses in Germany. Yet, they also find an increase in the gender employment gap. In their survey, 20 percent of parents with children that need care said they reduced working time because of child-care and home-schooling requirements in June 2020, and 13 percent said so in June. Also more mothers than fathers perceived the situation as "extremely/strongly stressful" during the pandemic.

4 A Closer Look at the United States

In this section, we provide a more detailed look at the case of the United States, the largest country in our study and the one with the largest gender gap in the employment impact of the pandemic.

4.1 Decomposition of Channels Underlying the Gender Gap

Building on the regression results in the previous section, we start by providing a decomposition analysis to asses the relative importance of the childcare and occupational channels for generating gender gaps in the impact of the pandemic. Given the results of Regression (4), the decomposition answers the following question: how much of the pandemic-induced change in the gender gap can be explained by the presence of children, and how much is due to industry and occupational effects? We apply this decomposition to the population of workers who were employed on the eve of the pandemic.[16]

An intuitive way to understand our decomposition is as follows: for each individual, we use the regression results in (4) to predict their pandemic-induced change in labor supply. Given the specification, this will depend on their gender, the presence of children, and their occupation. We then calculate the pandemic-induced change in the gender gap as the difference in the average change in labor supply for women and the average change in labor supply for men (in logs). Consequently, the aggregate change will depend on the micro effects (the estimated parameters $\boldsymbol{\theta}_2$, $\boldsymbol{\theta}_3$, and $\boldsymbol{\theta}_5$) and the joint distribution of characteristics—specifically gender, children, and occupations—in the population. For example, the contribution of the childcare channel is larger when more workers have a child. For our analysis we use the distribution of characteristics in the pre-pandemic data (i.e., $D_t = 0$). The decomposition then assigns aggregate changes associated with $\boldsymbol{\theta}_5$ to the labor demand channel. The childcare channel captures contributions from $\boldsymbol{\theta}_2$ and $\boldsymbol{\theta}_3$ relative to the effect on those with no kids. The residual accounts for any widening in the gender gap among workers with no kids that is not explained by occupation effects ($\theta_{3,\text{none}}$). Details on the derivation and implementation of this decomposition are provided in Appendix D.

Table 9: Decomposition of Pandemic-induced Change in the Gender Gap

Outcome	Childcare Channel	Occupation/Industry Channel	Residual
Employment	13.7%	12.4%	73.9%
Hours	17.7%	19.8%	62.5%

See Appendix D for details.

Table 9 gives the results. We find that about 14 percent of the gender gap in the employment decline and 18 percent in the hours decline can be attributed to the childcare channel. The occupational channel can account for 12 percent and 20 percent, respectively. These numbers imply that there is a large residual: two-thirds of the widening in the gender gap cannot be explained by the two channels. The size of the residual

[16]Workers who are out of the labor force for prolonged periods lack information on industry and occupation, so that a decomposition taking occupation effects into account is more informative for initially employed workers.

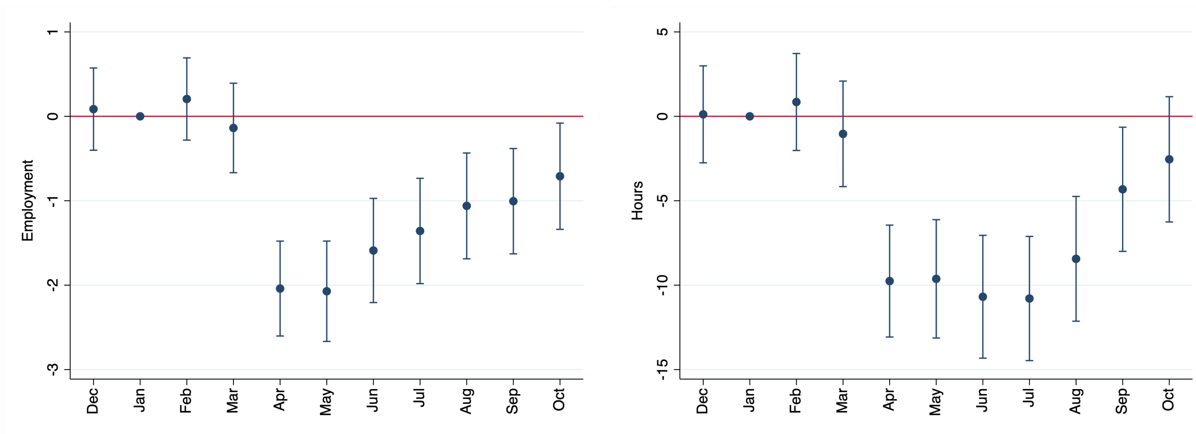
is likely related to a missing data problem: for many individuals who are temporarily not working, no information on occupation or industry is collected. This creates noise that likely reduces the measured contribution of the occupational channel. To assess the importance of this issue, we re-estimate our model on the sample of employed individuals only. Conditioning on employment means we can only decompose the intensive margin, as we are losing the extensive margin by construction. We do carry out this decomposition in Appendix D. The decomposition of the widening of the gender gap in hours (conditional on working) based on an estimation using employed workers only leads to a much smaller residual: we find that 21 percent of the gender gap can be attributed to the childcare channel and 50.5 percent to the occupational channel, leaving a residual of 28.5 percent. Note that while the occupation channel gains in importance, the contribution of the childcare channel is similar to the decomposition based on estimates for the entire sample.

Even a residual of just under 30 percent suggests that in the pandemic recession, there are channels beyond childcare and occupation that have a sizeable role in explaining the disparate effects of the pandemic on women and men. One possible channel is related to the gender wage gap. If families try to minimize family exposure to Covid-19, some family members may quit jobs or reduce hours to reduce the family's total infection risk. Such a behavior would make the most sense for family members with low earnings or working in high-contact occupations, such as women working as nurses, physical therapists, or grocery store clerks. A second possibility is that our estimate of the childcare channel understates the total effect because, for instance, it ignores the effects on grandmothers in multi-generational households, some of whom may also have reduced work in order to provide more childcare. Yet another possibility is that other care-giving responsibilities went up as women spent more time caring for elderly relatives and other family members.

4.2 The Impact over Time

Since for the United States we have monthly data through October 2020, we can estimate how the gender gap changes over time. To do so, we re-estimate Regressions (2) and (4), but instead of interacting the female and job effects with a pandemic indicator, D_t, we interact them with monthly time fixed effects. To add precision, we take advantage of the longitudinal dimension of the CPS data and include individual level fixed effects in the regression.[17] Also, we simplify child groups into a binary variable by combining parents of pre-K and school-age kids into one group. Those leaves us with two groups, those who have children under the age of 18 and those who do not. Results for the overall gender gap are depicted in Figure 8, and Figure 9 and 10 provide separate results for those with and without children. In each case, changes are reported relative to January 2020.

Figure 8: Change in the Gender Gap Over Time, December 2019 to October 2020



(a) Employment (b) Hours

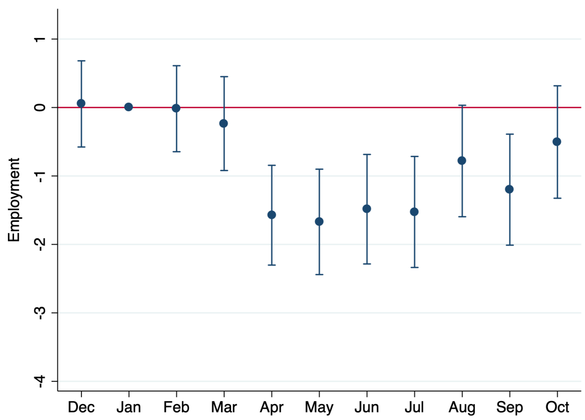
Notes: The figure displays changes in the gender gap in the United States relative to January 2020. Error bands represent 95 percent confidence intervals. See Appendix E for further details on the empirical specification.

Figure 8 shows that the gender gap was the largest early on in the pandemic. In April and May 2020, the gender gap was two percentage points higher compared to January in terms of employment, and ten percentage points in terms of hours. The employment gender gap started to narrow in June and had more than halved by October. The hours gap stayed wide for longer and started narrowing only in September. The decline over time of the gendered impact of the pandemic in the US has also recently been pointed out by Lee, Park, and Shin (2021).

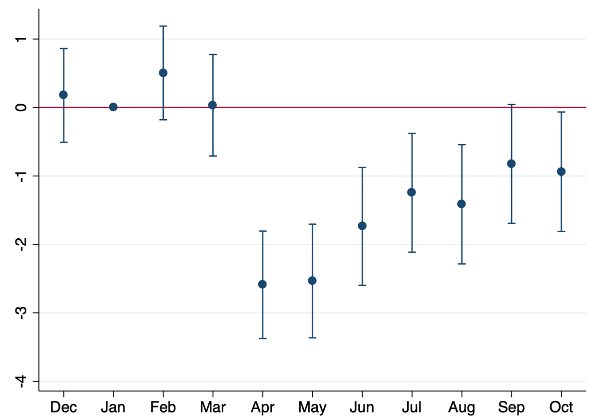
Figures 9 and 10 plot estimates over time for those with and without children. While both groups faced a widening of the gender gap in hours as well as employment due to the pandemic, in April and May 2020 the gender employment gap among parents had widened by almost three percentage points relative to January, compared to about two percentage points among non-parents. For hours worked, trends across those with and

[17]The time-trends and covariates in our benchmark model are now subsumed by the individual and time fixed effects. We continue to control for industry and occupation using non-parametric time trends by work type. More details on the specification can be found in Appendix E.

Figure 9: Change in the Employment Gender Gap by Presence of Children, December 2019 to October 2020



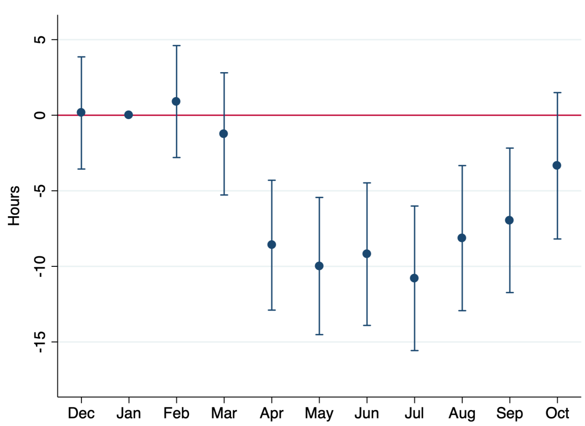
(a) no kids



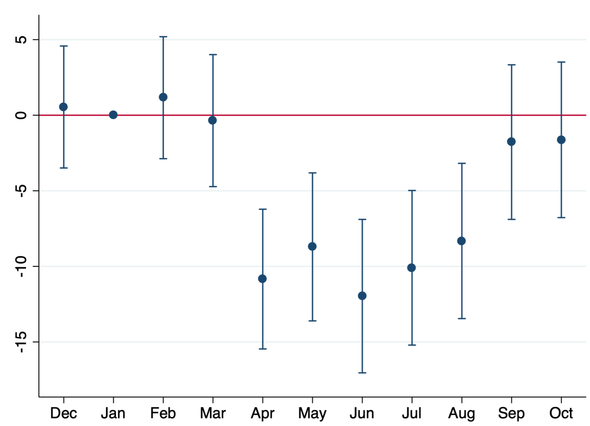
(b) with kids

Notes: The figure displays changes in the gender gap in the United States relative to January 2020. Error bands represent 95 percent confidence intervals. See Appendix E for further details on the empirical specification.

Figure 10: Change in the Hours Gender Gap by Presence of Children, December 2019 to October 2020



(a) no kids



(b) with kids

Notes: The figure displays changes in the gender gap in the United States relative to January 2020. Error bands represent 95 percent confidence intervals. See Appendix E for further details on the empirical specification.

without kids are similar. The gender gap in hours and employment declines over time, and by October 2020 the gender gap in employment remains statistically significant only among parents.

Generally, the impact of having children in the results displayed in Figures 9 and 10 is smaller compared to the raw data displayed in Figure 2 (and also Figure A4 in the appendix). Unlike Figure 2, the regressions underlying Figures 9 and 10 rely on micro data and include various controls, individual fixed effects, and differential trends across industries and occupations. Clearly, allowing for these controls and trends accounts for some of the raw gender gap displayed in Figure 2.

4.3 Pandemic Recession versus Great Recession

In our analysis of the micro data, we have so far focused entirely on outcomes during the pandemic recession. We have already established in Section 2 that the aggregate impact of the pandemic recession on women versus men is drastically different from regular recessions in a large set of countries, but this still leaves open the question of whether there are gender gaps related to parenthood and childcare in other recessions, too. To make one such comparison we focus on the contrast between the pandemic recession and the Great Recession of 2007-2009 in the United States.[18]

Table 10 provides results for the same specifications as in Tables 7 and 8 for the Great Recession in the United States. To focus on the first six months of the recession (as we do in Tables 7 and 8) we set the recession indicator D_t to one starting in December 2007 until May 2008. As expected given the results in Section 2, the table shows that, unlike the pandemic recession, the Great Recession was a mancession with larger declines in both hours and employment for men. Furthermore, the impacts on the gender gap among parents and non-parents are of the same sign and of a similar magnitude. These findings are consistent with the notion that both the overall impact on women in the labor market and the special role of parenthood are unique to the pandemic recession of 2020.

[18]We focus on the United States here because the overall impact of the 2007-2009 financial crisis on employment and the timing of the related economic downturn differed substantially across the countries we consider.

Table 10: Gender Gaps in Hours and Employment Changes during the Great Recession in the United States, December 2007 to May 2008

	Hours		Employment	
	benchmark	work controls	benchmark	work controls
Basic gender gap (β_3/γ_3)	10.13	3.39	1.88	0.39
	(0.00)	(0.00)	(0.00)	(0.01)
pre-K kids ($\delta_{3,\text{pre-K}}/\theta_{3,\text{pre-K}}$)	12.51	2.51	2.54	0.19
	(0.00)	(0.09)	(0.00)	(0.44)
school age kids ($\delta_{3,\text{school}}/\theta_{3,\text{school}}$)	8.08	3.12	1.40	0.34
	(0.00)	(0.01)	(0.00)	(0.10)
none ($\delta_{3,\text{none}}/\theta_{3,\text{none}}$)	10.37	3.64	1.92	0.44
	(0.00)	(0.00)	(0.00)	(0.01)

Notes: Coefficients reported are percentage points. Sample includes all civilians ages 25 to 55 who are either employed, unemployed or NILF. The p-values are reported in parentheses below estimates. Unless otherwise noted, all regressions include gender specific time trends and controls for age, education, race, and marital status, in addition to quarterly indicators and a fixed effect for education sector workers in summer months to control for seasonality. Child age brackets are assigned by the age of the youngest child (<5 and 5-17).

5 Heterogeneity by Education, Race, Single Parenthood, and Ability to Work from Home

We now return to the full set of countries and explore which other dimensions of heterogeneity (beyond parenthood and industry/occupation) are connected to gender differences in the labor market during the pandemic recession.

5.1 The Role of Education and Race

Consider, first, the role of education. Tables 11 and 12 present results analogous to Tables 7 and 8 with separate results for individuals with at least college education and less-educated workers.[19] The regressions in Tables 11 and 12 already include industry and occupation controls, and thus capture education effects beyond those that arise because education and work type are correlated.[20]

Recall that only the United States and Canada display a large and statistically significant overall gender gap for both employment and hours after controlling for industry and occupation effects (Tables 7 and 8). Tables 11 and 12 show that in the same two countries,

[19] We include a dummy indicating college education as an additional interaction term in our regression specifications (1)—(4). Hence, Tables 11 and 12 report the pandemic-induced gender gap interacted with the respective education level (and the presence of children).

[20] Tables A3 and A4 in the appendix display results without work type controls.

Table 11: Pandemic-induced Changes in the Gender Gap in Employment by Education, with Occupation/Industry controls

	USA	CAN	DEU	NLD	ESP	GBR
BA degree or higher (γ_3)	-0.52	-0.20	-1.92	1.71	0.01	-0.57
	(0.03)	(0.42)	(0.18)	(0.13)	(0.78)	(0.34)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-0.53	0.73		2.46	0.10	-0.28
	(0.20)	(0.08)		(0.22)	(0.23)	(0.79)
school age kids ($\theta_{3,\text{school}}$)	-1.82	-0.62	-1.95	-0.58	-0.08	-0.46
	(0.00)	(0.12)	(0.37)	(0.67)	(0.41)	(0.57)
no kids ($\theta_{3,\text{none}}$)	0.08	-0.51	-0.56	2.52	0.04	-0.99
	(0.80)	(0.09)	(0.75)	(0.06)	(0.45)	(0.19)
Less than BA degree (γ_3)	-1.59	-0.66	-0.83	0.44	0.05	-0.16
	(0.00)	(0.00)	(0.49)	(0.73)	(0.36)	(0.80)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-1.24	-0.32		-1.15	0.08	0.04
	(0.03)	(0.39)		(0.70)	(0.23)	(0.98)
school age kids ($\theta_{3,\text{school}}$)	-1.82	-2.34	0.28	0.77	-0.04	-0.84
	(0.00)	(0.00)	(0.89)	(0.67)	(0.67)	(0.31)
no kids ($\theta_{3,\text{none}}$)	-1.75	-0.31	-1.55	0.58	0.10	-0.38
	(0.00)	(0.23)	(0.27)	(0.69)	(0.20)	(0.62)

Notes: The notes of Table 7 apply. All regressions include occupation×industry controls interacted with the pandemic indicator. For details on the data, see Appendix C.

Table 12: Pandemic-induced Changes in the Gender Gap in Hours by Education, with Occupation/Industry Controls

	USA	CAN	DEU	NLD	ESP	GBR
BA degree or higher (γ_3)	-2.24	-5.38	-22.60	-17.57	-4.06	-4.23
	(0.10)	(0.00)	(0.15)	(0.15)	(0.08)	(0.27)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-4.79	-2.01		-71.19	-5.45	-0.82
	(0.07)	(0.42)		(0.01)	(0.31)	(0.90)
school age kids ($\theta_{3,\text{school}}$)	-7.66	-5.32	1.56	10.05	-8.11	-12.64
	(0.00)	(0.03)	(0.95)	(0.59)	(0.03)	(0.02)
no kids ($\theta_{3,\text{none}}$)	1.20	-5.46	-42.47	-15.26	-1.35	-5.15
	(0.49)	(0.00)	(0.01)	(0.35)	(0.65)	(0.30)
Less than BA degree (γ_3)	-7.75	-8.75	-21.56	-4.41	-0.81	4.46
	(0.00)	(0.00)	(0.10)	(0.73)	(0.70)	(0.22)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-3.22	-8.62		-50.31	5.16	14.65
	(0.26)	(0.00)		(0.23)	(0.26)	(0.03)
school age kids ($\theta_{3,\text{school}}$)	-9.86	-15.73	-14.63	-24.28	-2.46	-2.32
	(0.00)	(0.00)	(0.47)	(0.27)	(0.42)	(0.65)
no kids ($\theta_{3,\text{none}}$)	-8.49	-5.03	-23.73	7.89	-1.59	1.91
	(0.00)	(0.00)	(0.13)	(0.60)	(0.55)	(0.67)

Notes: The notes of Table 8 apply. All regressions include occupation×industry controls interacted with the pandemic indicator. For details on the data, see Appendix C.

the gender gap for both employment and hours is much larger among less-educated workers. In both countries, the gender gap for employment is more than three times larger among less educated workers compared to workers with college education. For hours, the gender gap among less educated workers is three times as large among the less educated in the United States, and a bit more than 50 percent larger in Canada. The role of childcare in accounting for these differences varies across countries. In the United States, it is notable that among college-educated workers, the gender gap in the impact of the crisis is entirely due to those with children—there is no significant gender gap for either employment or hours among those without kids. In contrast, among less educated workers women suffer larger declines in employment and hours even without children. In the United Kingdom (where the gender gap in the impact of the crisis is generally small) as well as in Spain the only group where we observe a large and statistically significant gender gap in the decline in hours worked consists of college-educated workers with school-age children.

Another salient dimension of heterogeneity is race; in the United States for example, overall employment losses have been substantially larger among Black and Hispanic compared to white workers. Tables 13 and 14 examine whether the gender gap in the impact of the crisis also varies across races. The underlying regressions include industry and occupation controls, and thus are not driven by differences in the distribution of workers of different races across work types.[21] Data on race is available only for the United States and the United Kingdom; for these countries, to maintain sufficiently large sample sizes we focus on differences between white workers and all others. For Canada, Germany, the Netherlands, and Spain we display analogous results focusing on differences between the native-born population and workers with a migration background (see Appendix C for details).

We find that in the United States, the gender gap is generally of a similar size between white and other workers. Having school age children expands the gender gap a bit more among white workers. Likewise, in the United Kingdom there are no significant differences in patterns between white and non-white workers. Notice that these results reflect relative changes between women and men; even though non-white workers generally experienced a larger reduction in employment and hours, this does not seem to affect women more strongly than men, and in the United States somewhat less so if they have school-age children.

[21] Tables A5 and A6 in the appendix display results without work type controls.

Table 13: Pandemic-induced Changes in the Gender Gap in Employment by Race or Migration Background, with Occupation/Industry Controls

	White / non-white		Migration background			
	USA	GBR	CAN	DEU	NLD	ESP
Gender gap: whites / no migration (γ_3)	-1.14	-0.32	0.20	-0.55	1.68	0.02
	(0.00)	(0.55)	(0.37)	(0.56)	(0.11)	(0.58)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-0.94	0.26	0.39		3.50	0.08
	(0.02)	(0.78)	(0.26)		(0.06)	(0.23)
school age kids ($\theta_{3,\text{school}}$)	-1.96	-0.75	-0.76	-0.09	1.12	-0.04
	(0.00)	(0.26)	(0.02)	(0.95)	(0.41)	(0.49)
no kids ($\theta_{3,\text{none}}$)	-0.91	-0.65	0.32	-0.62	1.65	0.05
	(0.00)	(0.30)	(0.19)	(0.59)	(0.16)	(0.33)
Gender gap: non-whites / migration (γ_3)	-0.93	-0.53	-1.88	-9.36	-0.69	0.10
	(0.01)	(0.61)	(0.00)	(0.01)	(0.67)	(0.37)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-0.33	-0.67	-0.48		-7.98	0.09
	(0.69)	(0.74)	(0.29)		(0.05)	(0.25)
school age kids ($\theta_{3,\text{school}}$)	-1.26	-0.68	-3.31	-8.11	-3.01	-0.09
	(0.04)	(0.68)	(0.00)	(0.10)	(0.26)	(0.66)
no kids ($\theta_{3,\text{none}}$)	-1.10	-0.95	-1.91	-9.22	1.37	0.22
	(0.02)	(0.53)	(0.00)	(0.05)	(0.49)	(0.17)

Notes: The notes of Table 7 apply. All regressions include occupation×industry controls interacted with the pandemic indicator. For Canada, Germany, the Netherlands, and Spain, we group people by migration background instead of race. For details on the data, see Appendix C.

Table 14: Pandemic-induced Changes in the Gender Gap in Hours by Race or Migration Background, with Occupation/Industry Controls

	White / non-white		Migration background			
	USA	GBR	CAN	DEU	NLD	ESP
Gender gap: whites / no migration (γ_3)	-5.20	-0.69	-5.42	-23.06	-4.59	-1.66
	(0.00)	(0.83)	(0.00)	(0.03)	(0.65)	(0.37)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-3.23	7.32	-3.33		-50.84	2.12
	(0.15)	(0.17)	(0.11)		(0.06)	(0.59)
school age kids ($\theta_{3,\text{school}}$)	-9.73	-9.82	-8.81	-11.96	-2.54	-4.54
	(0.00)	(0.02)	(0.00)	(0.47)	(0.88)	(0.08)
no kids ($\theta_{3,\text{none}}$)	-3.89	-1.93	-3.55	-28.95	1.31	-0.97
	(0.01)	(0.61)	(0.02)	(0.02)	(0.92)	(0.67)
Gender gap: non-whites / migration (γ_3)	-5.16	6.67	-10.79	-15.19	-31.52	-3.51
	(0.01)	(0.27)	(0.00)	(0.67)	(0.09)	(0.32)
pre-K kids ($\theta_{3,\text{pre-K}}$)	-4.79	5.34	-10.29		-123.02	-3.95
	(0.28)	(0.63)	(0.00)		(0.01)	(0.60)
school age kids ($\theta_{3,\text{school}}$)	-6.33	11.00	-16.79	4.13	-28.14	-6.27
	(0.05)	(0.26)	(0.00)	(0.93)	(0.44)	(0.30)
no kids ($\theta_{3,\text{none}}$)	-4.95	0.37	-6.66	-48.18	-16.85	-1.19
	(0.05)	(0.97)	(0.00)	(0.32)	(0.47)	(0.81)

Notes: The notes of Table 8 apply. All regressions include occupation×industry controls interacted with the pandemic indicator. For Canada, Germany, the Netherlands, and Spain, we group people by migration background instead of race. For details on the data, see Appendix C.

In Germany, the gender gap in the impact on employment is much larger among workers with a migration background. This difference is not driven by childcare: the gap is similar among workers with and without children. The same gap is not observed for hours. This suggests that among workers with an immigration background, women were more likely to lose their job in the crisis, whereas immigrant men and native workers were more likely to hold on to their job but then reduce hours through the use of furlough schemes. Some of this pattern may arise because many immigrant women have "minijobs" without formal employment protection. In the Netherlands, there is a substantial gender gap for both employment and hours among parents of young children with a migration background. In Canada, the gender gap among immigrants widens substantially for both employment and hours, particularly for those with school-age children. For non-immigrants we observe a similar effect for hours but of a smaller magnitude.

5.2 The Role of Single Parenthood

Our results so far indicate that childcare obligations are one major reason why women in many countries faced a deterioration in labor market opportunities during the crisis. The role of childcare suggests that single parents, who have less flexibility in sharing responsibilities with a partner, should be particularly exposed to the effects of the crisis. To examine this possibility, we now consider differences in the impact of the crisis on single mothers versus mothers living with a partner. The regressions take the form:

$$y_{it} = \boldsymbol{\kappa}_0\,\mathbf{Kid}_{it} + \boldsymbol{\kappa}_1\,\mathrm{S}_i \times \mathbf{Kid}_{it} + \boldsymbol{\kappa}_2\,\mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\kappa}_3\,\mathrm{S}_i \times \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\kappa}_4\,\mathbf{X}_{it} + \epsilon_{it}. \tag{5}$$

Here y_{it} is the outcome variable for individual i at time t, S_i is an indicator for a single mother, D_t is the indicator for the Covid-19 pandemic, and $\mathbf{Kid}_{it}$ is a vector of two dummy variables grouping households by age of their youngest child into two groups: pre-K (<5) and school age (5-17).[22] The vector $\mathbf{X}_{it}$ consists of the same control variables as in the earlier regressions. We run this regression on a sample consisting only of mothers with kids up to the age of 18 (below 20 in Spain); here we are interested in the coefficients $\boldsymbol{\kappa}_3$ on the interaction of S_i, D_t and $\mathbf{Kid}_{it}$, which captures the difference in the impact of the pandemic on single mothers versus mothers living with a partner by child age.

[22]In Spain, the group of school age children includes children up to the age of 19, based on the available age brackets in the Spanish micro data set.

We also carry out a version of this regression analogous to (4) with work type controls:

$$y_{it} = \boldsymbol{\lambda}_0 \, \mathbf{Kid}_{it} + \boldsymbol{\lambda}_1 \, \mathrm{S}_i \times \mathbf{Kid}_{it} + \boldsymbol{\lambda}_2 \, \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\lambda}_3 \, \mathrm{S}_i \times \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\lambda}_4 \, \mathbf{Job}_{it} + \boldsymbol{\lambda}_5 \, \mathbf{Job}_{it} \times \mathrm{D}_t + \boldsymbol{\lambda}_6 \, \mathbf{X}_{it} + \epsilon_{it}. \quad (6)$$

Table 15 shows the estimates of the parameters $\boldsymbol{\kappa}_3$ and $\boldsymbol{\lambda}_3$ in these regressions. In the results without work type controls, we find that in the United States, Canada, and Spain single mothers of school-age children experienced larger declines in employment and hours compared to mothers living with a partner. In the United States and Canada, the same is true for single mothers of younger children. In contrast, in Germany, the Netherlands, and the United Kingdom there are no significant differences in the impact of the crisis on single versus other mothers.

The results controlling for work type indicate that a lot of the large impact on single mothers in the United States, Canada, and Spain is due to the fact that single mothers are likely to have jobs in industries and occupations that experienced larger employment declines in the crisis. In all three countries, the gap between single mothers and mothers living with a partner is substantially reduced once differential trends across job types are controlled for. In the United States, in fact, all differences become statistically insignificant. In Canada, the additional impact on single mothers remains quantitatively large even after controlling for work type. For example, hours for single mothers decline by an additional 5.1 percentage points for mothers of school-age children, and by 14.4 percentage points for mothers of younger children. In Spain, we observe a similarly strong decline in hours for single mothers of school-age children by an additional 9.2 percentage points when taking work type into account. In the Netherlands the impact on the employment of single mothers with school-age kids is larger after controlling for work type.

The results provide support for the view that single mothers faced particularly large challenges during the crisis, but also show that local conditions matter. The extent of school closures and the availability of emergency childcare varied widely across the countries considered. So does mothers' baseline labor supply. In Germany and the Netherlands, for example, relatively few mothers work full time, which may give them additional flexibility to deal with childcare needs compared to otherwise similar mothers in the United States or Canada who where working full time at the beginning of the

Table 15: Pandemic-induced Changes in Labor Supply for Single Mothers

	USA	CAN	DEU	NLD	ESP	GBR
Single mothers employment gap						
pre-K kids ($\kappa_{3,\text{pre-K}}$)	-5.67	-3.69		4.82	-0.03	-2.64
	(0.00)	(0.00)		(0.54)	(0.99)	(0.29)
school age kids ($\kappa_{3,\text{school}}$)	-1.44	-2.04	6.80	-2.15	-2.82	0.85
	(0.03)	(0.00)	(0.11)	(0.42)	(0.02)	(0.51)
w/ ind & occ controls						
pre-K kids ($\lambda_{3,\text{pre-K}}$)	-0.14	-0.48		5.73	0.10	0.56
	(0.82)	(0.38)		(0.39)	(0.36)	(0.80)
school age kids ($\lambda_{3,\text{school}}$)	0.28	-1.02	7.59	-4.52	-0.27	0.58
	(0.50)	(0.00)	(0.08)	(0.03)	(0.12)	(0.57)
Single mothers hours gap						
pre-K kids ($\kappa_{3,\text{pre-K}}$)	-25.09	-28.10		43.64	-4.08	-15.15
	(0.00)	(0.00)		(0.58)	(0.73)	(0.09)
school age kids ($\kappa_{3,\text{school}}$)	-12.59	-10.99	68.71	23.20	-22.20	-2.57
	(0.00)	(0.00)	(0.18)	(0.43)	(0.00)	(0.67)
w/ ind & occ controls						
pre-K kids ($\lambda_{3,\text{pre-K}}$)	-1.51	-14.40		14.41	-5.27	2.72
	(0.64)	(0.00)		(0.86)	(0.53)	(0.75)
school age kids ($\lambda_{3,\text{school}}$)	-3.20	-5.06	84.68	7.54	-9.21	3.26
	(0.13)	(0.03)	(0.10)	(0.77)	(0.01)	(0.54)

Notes: Hours coefficients reported are log points difference of the pandemic's effect on single mothers versus non-single mothers. Employment coefficients are percentage points difference. Sample includes all mothers with children (aged <5 or 5-17, by youngest child) aged 25 to 55 who are not in the military. In Spain, the group of school-age children includes those up to the age of 19. For Spain, Germany and the UK we use cohabitation-marriage status (=1 if married or cohabiting, =0 if neither cohabiting nor married). Otherwise, all notes from Tables 7 and 8 apply. For further details on the data, see Appendix C.

crisis. We also note that for the Netherlands and Germany we have only few observations of single mothers, making it more difficult to reliably identify the role of single motherhood in these countries.

5.3 The Role of the Ability to Work from Home

We already saw that the impact of the pandemic on workers varied widely across industries and occupations. Among the underlying job characteristics that give rise to these differences, arguably the most important one is the ability to work from home. Job losses were highest in industries and occupations were working from home is impossible, including much of the hospitality industry. In contrast, other groups such as office workers and academics were able to continue work via telecommuting, and rapidly adopted remote-working tools such as videoconferencing on Zoom and similar services in the process. The ability to work from home also interacts with childcare needs; looking after children in virtual school is easier for a parent who is working on a laptop a few feet away compared to a parent who has to commute to a workplace.

To examine how telecommuting shaped the labor market experiences of women versus men during the pandemic, we now consider how the gender gap in the impact of the crisis differs between workers who are able to work from home during the pandemic and those who are not. We focus on the United States, the United Kingdom, and the Netherlands, where information on telecommuting during the crisis is available. Moreover, we limit attention to the intensive margin of labor supply (hours worked conditional on being employed), because the place of work is only known for the employed.

For the United States, information on telecommuting during the pandemic is available from the Covid-19 supplement to the CPS.[23] The answers are available starting in May 2020, and we classify individuals as telecommuting if they worked remotely at any point from May 2020 to September 2020. We retrieve labor market outcomes predating May 2020 using the panel dimension of the the CPS monthly files. In the United Kingdom, telecommuting information is available for all employed individuals, including those who report zero hours of work (i.e., workers on furlough). Note that our information is on actual telecommuting rather than just the ability to work from home, so that results could be influenced by workers' decision whether to work from home if they have the

[23]The relevant question is as follows: "At any time in the last 4 weeks, did (you/name) telework or work at home for pay because of the coronavirus pandemic? (Enter No if person worked entirely from home before the Coronavirus pandemic)"

ability to do so. Nevertheless, we conjecture that during the crisis most workers who were able to work from home actually did so. In the Netherlands, the data contains information on the hours worked from home in the reference week for March, April, May, June, and September 2020. Hence, we follow the same approach as for the United States and define individuals to be able to telecommute if they have been working from home at any point between March and September 2020.

Table 16: Pandemic-induced Change in the Gender Gap in the Intensive Margin of Employment by Telecommuting Status

	United States		United Kingdom		The Netherlands	
	benchmark	work type	benchmark	work type	benchmark	work type
No telecommuting (β_3/γ_3)	-12.42	-11.87	-1.00	-2.18	6.19	7.96
	(0.00)	(0.00)	(0.74)	(0.49)	(0.69)	(0.64)
pre-K kids ($\delta_{3,\text{pre-K}}/\theta_{3,\text{pre-K}}$)	-17.18	-17.33	-3.02	-4.39	-66.07	-60.23
	(0.00)	(0.00)	(0.58)	(0.43)	(0.21)	(0.24)
school age kids ($\delta_{3,\text{school}}/\theta_{3,\text{school}}$)	-14.89	-14.09	-10.70	-9.01	-13.44	-19.01
	(0.00)	(0.00)	(0.01)	(0.04)	(0.64)	(0.51)
no kids ($\delta_{3,\text{none}}/\theta_{3,\text{none}}$)	-9.45	-8.76	2.93	-0.15	18.81	22.48
	(0.00)	(0.00)	(0.43)	(0.97)	(0.33)	(0.29)
Telecommuting (β_3/γ_3)	-3.60	-2.07	9.35	12.80	-11.99	-12.32
	(0.06)	(0.29)	(0.08)	(0.02)	(0.27)	(0.30)
pre-K kids ($\delta_{3,\text{pre-K}}/\theta_{3,\text{pre-K}}$)	-3.52	-1.47	12.82	18.47	-41.71	-49.50
	(0.34)	(0.69)	(0.28)	(0.11)	(0.13)	(0.08)
school age kids ($\delta_{3,\text{school}}/\theta_{3,\text{school}}$)	-4.51	-2.90	3.50	9.95	-3.23	4.87
	(0.09)	(0.28)	(0.67)	(0.22)	(0.86)	(0.80)
no kids ($\delta_{3,\text{none}}/\theta_{3,\text{none}}$)	-3.51	-2.27	13.25	12.85	-7.60	-12.32
	(0.11)	(0.32)	(0.08)	(0.08)	(0.61)	(0.42)

Notes: Coefficients reported are log percentage point differences of the pandemic's effect on women versus men. Sample includes all civilians aged 25 to 55 who are employed (in the US restricted to positive hours, in the UK including those with zero hours, e.g. those on furlough). The p-values are reported in parentheses below estimates. All regressions include gender specific time trends and controls for age, education, race, and marital status, in addition to quarterly indicators and a fixed effect for education sector workers in summer months to control for seasonality. Child age brackets are assigned by the age of the youngest child (<5 and 5-17). For details on the data, see Appendix C.

Table 16 displays how the gender gap in the impact of the crisis differs between workers who can work from home and those who cannot. For the United States, the result is straightforward to summarize: there are large gender gaps among workers who are unable to work from home but only small ones among telecommuters, which become insignificant when controlling for work types. This continues to be true when we separate results between parents and others. Among telecommuters, gender gaps are small among both parents and non-parents. In contrast, among non-telecommuters, there is a large gender gap even among workers without kids, and an even larger one among parents. Unlike in our baseline results that do not control for telecommuting, this time the largest gender gap is found among parents of young (pre-K) children: in this group, mothers are estimated to reduce hours by about 17 percentage points more than fathers do. Among parents of school-age children the gender gap amounts to 14 percentage points, versus 9 percentage points among those without kids under the age of 18. Interestingly, the results are essentially the same regardless of whether we also introduce job type controls or not. This suggests that the ability to work from home is the main job-type characteristic that matters during the pandemic, so that few additional effects arise when telecommuters and non-telecommuters are already separated.

Table 17: Hours Worked during the Pandemic in the United States by Telecommuting, Gender, and Children

	Women		Men	
	Non-Tele	Telecommute	Non-Tele	Telecommute
No or adult children	35.2	37.9	39.1	39.9
Pre-K children	30.0	35.2	40.3	40.4
Middle school children	32.5	36.6	40.5	41.5
High school children	34.1	36.8	40.6	41.4

Notes: Sample includes all employed individuals, ages 25-55, not in the military. Report values correspond to weighted average hours worked last week by sex, child group, and telecommuting status from May 2020 through Oct 2020. Child age brackets are assigned by the age of the youngest child (pre-K: <5, middle school: 5-13, high school: 14-17).

The central role of the combined effect of the ability to work from home and childcare needs is also apparent from the raw data on labor supply for women and men during the pandemic. Table 17 displays average hours worked conditional on being employed in the United States broken down by gender, parental status, and telecommuting. For men, weekly work hours vary little across these groups and are close to 40 hours per week in each case. Similarly, for women who can telecommute labor supply is roughly constant across groups, with all groups averaging between 35 and 38 hours per week. For women who cannot telecommute, however, motherhood makes a big difference: non-telecommuting mothers of pre-K children work more than 5 hours less per week during the pandemic compared to non-telecommuting women without children. For mothers of middle school children, there is still a gap of about 3 hours per week.

In the Netherlands, we observed in our baseline regression a large and significant gender gap in hours for parents with pre-K kids (see Table 8). The coefficients in Table 16 suggest that this result is to some extent driven by those parents who cannot telecommute. In this group, we observe a stark contrast between those with small children and those without children, although the results are not tightly estimated due to small sample size.

Regarding the United Kingdom, recall that unlike the other countries considered here we did not find a substantial gender gap in the impact of the crisis. Once we separate out telecommuters, most gender-gap coefficients in Table 16 continue to be small and statistically insignificant. However, we now do find a sizeable gender gap among workers who cannot telecommute and who have school-age children. In this group, the negative impact on the labor supply of mothers is 9 to 11 percentage points larger compared to fathers. Thus, even in the United Kingdom the combination of having to look after school age children and being unable to work from home is associated with a large decline in mothers' labor supply.

The gender gap among parents of school-age children in the United Kingdom is related to the use of furlough schemes; there are more mothers than fathers recorded as employed but working zero hours.[24] Furloughing accounts for most of the gender gap in labor supply of non-telecommuting parents with school-age children: if we exclude those who record zero hours, the gender gap turns insignificant.[25] Hence, the data suggests that furlough schemes gave workers additional flexibility in dealing with the crisis, and that it was mothers of school-age children who used this flexibility to select into not working temporarily (i.e., asking their employer to be furloughed if telecommuting was not an option).[26]

Table 18 provides a further breakdown of the results of Table 16 for the United Kingdom by allowing for separate interactions for more educated (BA degree or higher) and less educated (less than BA) workers. Here we see that the option to telecommute in the pres-

[24]The percentage point difference between mothers and fathers with a school-age child reporting zero hours while being employed increases from 2.2 percentage points in Q1/2020 to 5.2 percentage points in Q2/2020 and even further to 7.8 percentage points in Q3/2020. For those with pre-K children, there is always a sizeable gender gap in those employed but working zero hours (18.5 percentage points in Q1/2020), likely due to generous parental leave policies. For this group we also observe an increases, but it is less pronounced: 18.5 percentage points in Q1/2020, 19.2 percentage points in Q2/2020, and 21.7 percentage points in Q3/2020. In contrast, the difference is stable for those without kids: 2.0 percentage points in Q1/2020, 1.5 percentage points in Q2/2020, and 2.3 percentage points in Q3/2020.

[25]In fact, if we exclude those who report zero hours, the impact of the pandemic on the gender gap decreases in absolute value from -10.7 to -1.0 and once we control for work type from -9.0 to -0.7.

[26]Adams-Prassl et al. (2020a) indeed find that UK mothers were more likely to initiate furloughing than fathers (as opposed to the employer), while no such gender gaps were found among childless workers.

ence of children matters a lot more for highly educated mothers. Among telecommuting workers with at least BA education there is no significant gender gap in the impact of the crisis regardless of having children. In contrast, the gender gap among educated parents who cannot work from home is large. Depending on the age of the children and on whether we control for additional occupation and industry effects, the labor supply of non-telecommuting educated mothers falls by 13 to 20 percentage points more than the labor supply of fathers in this group. Among less educated workers, these gender gaps are small or non-existent. Thus, even though overall the gender gap in the impact of the crisis is small in the United Kingdom, even here we find that the clash of childcare needs and having to be at work during the crisis was a challenge for many mothers.

Table 18: Pandemic-induced Change in the Gender Gap in the Intensive Margin of Employment in the United Kingdom by Telecommuting Status and Education

	Benchmark		w/ occupation x industry	
	Less than BA	BA or higher	Less than BA	BA or higher
No telecommuting (β_3/γ_3)	0.40	-7.97	2.83	-7.62
	(0.91)	(0.03)	(0.47)	(0.04)
pre-K kids ($\delta_{3,\text{pre-K}}/\theta_{3,\text{pre-K}}$)	1.53	-14.54	5.72	-12.62
	(0.84)	(0.05)	(0.46)	(0.09)
school age kids ($\delta_{3,\text{school}}/\theta_{3,\text{school}}$)	-7.96	-19.76	-3.11	-17.78
	(0.14)	(0.00)	(0.58)	(0.00)
no kids ($\delta_{3,\text{none}}/\theta_{3,\text{none}}$)	3.75	-3.02	3.72	-4.03
	(0.43)	(0.54)	(0.44)	(0.41)
Telecommuting (β_3/γ_3)	3.88	6.63	6.43	17.74
	(0.60)	(0.35)	(0.38)	(0.01)
pre-K kids ($\delta_{3,\text{pre-K}}/\theta_{3,\text{pre-K}}$)	-8.76	22.34	-2.66	34.13
	(0.63)	(0.14)	(0.88)	(0.02)
school age kids ($\delta_{3,\text{school}}/\theta_{3,\text{school}}$)	-2.83	-1.80	2.91	14.32
	(0.80)	(0.87)	(0.79)	(0.21)
no kids ($\delta_{3,\text{none}}/\theta_{3,\text{none}}$)	14.95	6.22	12.52	13.41
	(0.15)	(0.55)	(0.22)	(0.18)

Notes: Coefficients reported are log points difference of the pandemic's effect on women versus men. Sample includes all civilians aged 25 to 55 who are employed (including those with zero and positive working hours in the last week). The p-values are reported in parentheses below estimates. All regressions include gender specific time trends and controls for age, education, race, and marital status, in addition to quarterly indicators and a fixed effect for education sector workers in summer months to control for seasonality. Child age brackets are assigned by the age of the youngest child (<5 and 5-17). For details on the data, see Appendix C.

Overall, our results suggest that the ability to work from home played a central role in shaping the impact of the pandemic on working women. Being able to telecommute is a clear advantage for all workers during the pandemic, both because this reduces the probability of employment loss and because working at home reduces the risk of exposure to disease. Parents get the additional benefit of having an easier time dealing with additional childcare and supporting their children's education during school and daycare closures. While this benefit in principle accrues to both fathers and mothers, our results show that in practice it was primarily women's employment that suffered where a conflict between children's needs and a lack of ability to telecommute arose.

6 The Impact of the Pandemic on Workers' Productivity

So far we have focused on labor supply to document inequality in the impact of the pandemic on the labor market. While we find a lot of evidence of gender inequality during the crisis, we also document that workplace flexibility in the form of the ability to work from home appears to protect women's labor market prospects. This could be taken as a hopeful sign for the long-run impact of the pandemic on gender inequality. The recent literature on the "motherhood penalty" shows that the combined challenge of career and family goals is at the root of much of the gender inequality in the labor market today. Our results suggest that workplace flexibility substantially reduces the conflict between work and childcare. Moreover, now that many employers have adopted working-from-home, liked the results, and plan to preserve work-from-home options in the future, we can expect that after the pandemic workplace flexibility will be much more widely available than previously. Should we therefore expect a smaller motherhood penalty and lower gender gaps in the post-pandemic labor market?

While such an outcome of lower future gender equality is a possibility, our evidence on labor supply may paint an incomplete picture of the impact of the crisis on working women and men. Even though working from home allowed many parents to continue working while also supervising their children, productivity at work may still have suffered in the process. Moreover, if the division of childcare duties is unequal in the family, the productivity impact may be more severe for mothers than for fathers. The evidence indeed suggests that on average, mothers provided the larger share of the additional childcare during the pandemic. For example, Adams-Prassl et al. (2020b) show that during the pandemic women with children who worked from home spent one to two hours more every day on childcare and home schooling compared to men in the same situation, with remarkably similar patterns in the United States, Germany, and the United Kingdom.[27] This evidence suggests that combining working from home with

[27] See also Zamarro and Prados (2021) for additional evidence for the United States.

childcare was a greater challenge for mothers compared to fathers.

Table 19: Working from Home while Looking after Children in the Netherlands, April 2020

	Hours worked from home per week	Percent of home work hours also spent on childcare	Percent of all work hours also spent on childcare
All parents	13.0	61.1	30.8
Single parents	12.9	64.3	32.6
Mothers, kids 1-5	9.9	59.4	34.8
Fathers, kids 1-5	17.2	49.5	26.1
Mothers, kids 6-14	11.1	76.0	38.7
Fathers, kids 6-14	15.4	58.5	27.7
Mothers, kids 15-18	8.8	54.6	22.9
Fathers, kids 15-18	19.8	51.7	24.3

Notes: See Appendix C.4 for details.

Our data for the Netherlands provides direct evidence of a greater clash between work and childcare responsibilities for women compared to men. Table 19 shows that in April 2020, Dutch parents spent on average 13 hours per week working from home. A lot of this time was combined with childcare: averaging between mothers and fathers, parents report that for more than 60 percent of the time working at home they were simultaneously looking after their children. However, there is a large gender gap in doing double duty. In line with our other results, this gender gap is largest for those with school-age children (ages 6–14) who likely need help with home schooling. In this group, mothers spent three quarters of their work time at home on simultaneously taking care of children, which is 30 percent more than the fathers in this group. As a fraction of all work hours (including those done outside the home), mothers of school-age children spent close to 40 percent of work time on also doing childcare, about 40 percent more than fathers did.

Andrew et al. (2020a) provide additional evidence of a gender gap in doing double duty of work and childcare based on a survey of parents in the United Kingdom carried out in April and May 2020. The authors find that mothers generally spent more time on childcare and house work and less time on paid work compared to fathers. To assess the extent to which other responsibilities such as childcare affect the quality of the time spent working, the authors focus on work interruptions, defined as doing at least one non-work activity during an hour of paid work. Whereas prior to the pandemic, both mothers and fathers used to be interrupted proportionally to their work hours, during the crisis mothers are interrupted about 50 percent more often. For mothers, 90 percent of these interruptions are due to childcare. Overall, fathers working for pay ended up with nearly twice as many uninterrupted work hours compared to mothers working for pay.

This evidence suggests even though working from home may have cushioned the impact of school and daycare closures on employment, the quality of parents' work time and productivity are likely to have suffered in the process. This impact is much larger for mothers than for fathers. Lower productivity at work, in turn, may have implications for human capital accumulation on the job and future career prospects. While in some occupations a short-run dip in productivity may be of little concern, in others mothers with high childcare obligations during the crisis may miss out on raises or promotions in the near future. In "up-or-out" occupations such as law, falling behind peers during the crisis could put up a permanent ceiling to future career prospects.

For the most part, the productivity losses of working parents during the pandemic will show up in the data only some years down the road. There is one sector characterized by "up-or-down" promotions where evidence on productivity during the crisis is already available: academia. The productivity of academic researchers can be proxied by real-time output measures such as publications and working papers. Several recent research papers document a gender gap in researchers' productivity since the beginning of the pandemic. Amano-Patiño et al. (2020) use data from the NBER and CEPR working paper series and the "CEPR Covid Economics: Real-Time and Vetted Papers" online journal to analyze the contribution of female economists during the first wave of the pandemic. They find that while the relative number of female authors remained constant at about 20 percent, women constituted only 12 percent of all authors working on Covid-19 research. Since Covid-19 research was carried out during the pandemic, while most other working papers were likely based on research started well before the onset of the pandemic, this suggest a sizeable decline in the relative research productivity of women. Similarly, Ribarovska et al. (2021) document a small reduction in female last authors in a neurology journal, and a much larger reduction of female first and last authors among articles in a COVID-19 special issue. Kim and Patterson (2020) analyze Twitter posts by academic political scientists between June 2019 and June 2020 and find a larger decline in work-related tweets for women compared to men. The authors argue that this gender gap is likely driven by increased family obligations, since at the same time female researchers became relatively more likely to tweet about family-related matters. Barber et al. (2021) use a survey of members of the American Finance Association to examine determinants of research productivity during the pandemic, and find that productivity fell more for women and for researchers with young children.

Many universities have announced policy changes to respond to the challenge that the crisis poses for young researchers, such as tenure-clock extensions for assistant professors. However, with few exceptions these polices do not distinguish between women and men or make special provisions for researchers with major childcare responsibilities during the crisis. Given the emerging evidence of a relative productivity decline of women in academia, the likely result is a deterioration of many female researchers' relative prospects for tenure and career advancement. Given the broader evidence of a more severe clash between work and childcare responsibilities for mothers compared to fathers during the pandemic, it is likely that similar repercussions will occur in other industries and occupations, although it will take some time until it will be possible to verify this in the data.

7 What Have We Learned and Why Should We Care?

What general lessons can be learned from our analysis of data on labor market outcomes for women and men during the coronavirus pandemic? Even though there are a lot of differences across countries, a few common themes emerge. In this section, we summarize our findings and discuss what they imply for how differences in the impact on working women and men matter for economic outcomes during the crisis and beyond.

7.1 Summarizing the Findings

The main conclusions arising from our empirical analysis are as follows:

1. **The pandemic recession is a shecession (almost) everywhere.** Figure 4 shows that in 18 out of 28 advanced economies women's employment fell by more than men's during the pandemic, and in 19 out of 28 countries women experienced a larger decline in hours worked. What is more, even in countries where the impact

on women and men was similar, this still presents a sharp deviation from usual recessions, which tend to be mancessions in most countries. Figure 5b shows that in all but two countries (Ireland and Sweden) the negative impact of the recession on women's hours worked relative to men's was larger than what would be expected based on earlier recessions. Overall, we conclude that the unusually large impact of the pandemic recession on working women is a common feature among a large set of economies, and a key distinction between this and earlier recessions.

2. **Industry/occupation effects and childcare needs are the main, but not the only, cause of gender gaps.** Figure 6 demonstrates that in many countries, the pandemic recession had an unusually large impact on industries with high female employment shares, such as leisure and hospitality. Tables 7 and 8 show that in the countries with significant gender gaps in the impact of the pandemic on employment or hours the gender gap is usually substantially reduced when controlling for different trends across industries and occupations. The same tables show larger gender gaps among parents of school-age children, indicating the importance of childcare and home schooling obligations. Nevertheless, gender gaps go beyond industry/occupation and childcare effects. Tables 7 and 8 show that in countries where there are statistically significant overall gender gaps in the impact of the pandemic on employment or hours, a substantial and statistically significant gap is observed even among workers without children and after controlling for industry/occupation effects. The decomposition analysis for the United States in Section 4 shows that the childcare and industry/occupation channels account for less than half of the total gender gap. Clearly, there are additional factors that made women's employment more vulnerable in the pandemic, and understanding these factors is an important challenge for future research on the pandemic recession.

3. **Gender gaps during the pandemic recession vary widely across countries.** While qualitatively in most countries the pandemic recession is a shecession, quantitatively there is wide variation in the gaps between the impacts on women and men across countries (see Figure 4). What is more, there is only a loose correlation between the impact of the gender gap in terms of employment and hours. The United States is an example of a country with a large gender gap in the decline in employment, yet hours worked relative to men changed less than in other countries. In contrast, in countries such as Denmark and Germany, women experienced fewer

employment losses than men, but also a large reduction in relative hours worked, implying that women's labor supply conditional on working dropped sharply.

4. **Policy difference likely contributed to cross-country differences in the impact of the crisis, but evidence is inconclusive.** The policy response to the pandemic varied widely across countries, for example in terms of the severity and duration of lockdowns and the extent and duration of school closures. Given that much of the pandemic recession is due to the response of the crisis rather than a direct consequence of disease, one would expect that policy differences contribute to cross-country variation in gender gaps. Tables 2 and 3 show that the extent of school closures is indeed correlated with employment losses during the pandemic across countries. However, there is no conclusive evidence that these policy differences underlie cross-country differences in gender gaps (Tables 4 and 5). Another relevant policy dimension is the use of furlough policies (such as *Kurzarbeit* in Germany) to protect employment during the crisis. Tables 7 and 8 show that in Germany there is only a small effect on overall employment and no gender gap in this dimension, but a large overall impact and a large gender gap in hours. The United States, with little use of furlough policies, the overall impact and gender gaps are much larger in terms of employment and smaller in terms of hours. These observations suggest that furlough policies in Germany protected formal employment relationships while also providing flexibility for large adjustments of labor supply on the intensive margin.

5. **Work flexibility in the form of the ability to work from home greatly reduces the impact of the pandemic on gender gaps.** Table 16 shows that in the United States and the United Kingdom, there is no statistically significant larger impact on women's hours worked among workers who can work from home during the crisis, regardless of industry, occupation, or childcare obligations. Table 4 shows that the fraction of jobs that allow for telecommuting is the only variable that is significantly correlated with differences in the gender gap across countries. This evidence suggests that work flexibility greatly reduces gender differences in the labor market during the pandemic. However, there is evidence that among those working from home, mothers experienced a larger decline in productivity while simultaneously engaging in work and childcare. Table 19 shows that in the Netherlands, mothers working from home spent a much larger fraction of the work time while also looking after their children than fathers did. Survey evidence for other

countries and direct productivity measures for academic research also suggest a larger dip in women's work productivity during the pandemic.

7.2 Wider Implications for the Nature of the Pandemic Recession

Is a shecession the same as a mancession with signs reversed? For sure, the simple issue of whether the bulk of employment losses falls on women rather than men is a big part of what makes these types of recessions distinct. But there are equally important qualitative differences between shecessions and mancessions. Understanding these differences matters for policy tradeoffs during the recession and for the shape of the economic recovery that follows.

A first qualitative difference between shecessions and mancessions arises from the different dynamic behavior of women's and men's labor supply. Women's labor supply is generally more elastic at the micro level (e.g., Blundell and MaCurdy 1999). Men's labor supply elasticity is lower, and particularly so for married men. This implies that when men lose employment in a recession, they are likely to stay in the labor force and return to full-time employment in the recovery. In contrast, given their more elastic labor supply, when losing employment in a recession women are relatively more likely to drop out of the labor force or to only seek part-time work. At the economywide level, these patterns suggest that in a shecession, when job losses are concentrated on women, the decline in aggregate labor supply will be more persistent, and continue to be concentrated on women during the recovery (see Alon et al. 2020b for a quantitative analysis making this point).

A second difference between shecessions and mancessions relates to insurance within the household. Married couples can provide each other with insurance for income shocks. The mere presence of a second earner implies that a temporary job loss has a smaller proportional impact on earnings compared to single-earner households. Couples are also able to provide each other with active insurance, such as the "added worker effect" of a secondary earner joining the labor force in response to unemployment of the primary earner (Lundberg 1985). Blundell, Pistaferri, and Saporta-Eksten (2016) show that within-family insurance is the primary insurance channel for many households, and Bardóczy (2020) argues that this insurance channel plays a central role in the transmission of aggregate shocks.

The distinct behavior of women's and men's labor supply suggests that family insurance is less effective in the pandemic recession compared to a regular recession. The large overall impact on the employment of both women and men implies that there are many families where both husband and wife experience earnings losses, which reduces the scope for passive insurance. More importantly, active insurance relies on the ability of the spouse who did not experience unemployment or reduced earnings to increase labor supply. In a mancession, the spouse who provides insurance is usually the wife. More married women than men work either part time or are out of the labor force, which means that there is scope for increasing labor supply. Therefore, in a mancession active insurance can play an important role in buffering income losses for households. In contrast, when married women lose employment in a shecession, their husbands are often unable to provide active insurance, because they already work full time and because married men's labor supply is generally inflexible. Overall, family insurance is much less effective in a shecession such as the current pandemic recession compared to a regular recession.

Beyond shaping labor supply responses, the lack of family insurance also matters for how aggregate consumption and savings evolve in the recession. If households have less access to insurance, economic shocks translate more directly into consumption. The strength of this transmission can be summarized by the marginal propensity to consume (MPC), which is the fraction of a one-dollar loss in income for a household that will be reflected in lower consumption in the same period (instead of in lower savings). Alon et al. (2020b) show that the loss of family insurance in a pandemic recession results in a sustained raise in MPCs relative to a regular recession. Higher economywide MPCs, in turn, can result in a deeper recession and in a slower recovery, because higher MPCs mean that aggregate demand will drop more sharply during the recession. To be sure, a pandemic recession has additional implications for MPCs that do not relate to the relative impact on women's versus men's employment, for example because of reduced consumption opportunities during lockdowns and the effects of stimulus payments during the crisis. Depending on policy responses the overall evolution of MPCs in a pandemic recession is therefore ambiguous, but the family insurance channel is a force towards higher MPCs in this type of recession.

There are also opposing channels that suggest less severe effects of shecessions compared to mencessions. First, employed women work on average fewer hours than employed men. Hence, the same employment losses in a shecession will lead to lower aggregate hours losses than a mancession of the same size (when measured by employment declines). Second, women on average earn less than men, so even the same hours losses in a shecession will lead to lower GDP declines compared to a mancession with the same aggregate hours losses. Third, one might argue that women's more elastic labor supply arises because of better alternative uses for their time, e.g., home production rather than playing video games (Aguiar et al. 2020). While this point is surely debatable, it suggests the possibility that the welfare losses of job loss differ between women and men. Relatedly, domestic violence generally goes up in recessions (Siflinger, Tertilt, and van den Berg 2012) and one might hypothesize that this would be less true in shecessions. However, due to the pandemic-induced lockdowns which put stress on families, studies in fact do find an increase in domestic violence (Leslie and Wilson 2020; Bullinger, Carr, and Packham). But it is possible that other side effects of recessions, such as increases in the crime rate or drug abuse are less pronounced in shecessions. Further data will be needed to evaluate such hypotheses empirically.

The impact of the pandemic recession on women's employment also matters through its interaction with policies and institutions. In many countries unemployment insurance is the primary social insurance channel in recessions. However, women who stop working during the pandemic because of childcare needs are usually out of the labor force rather than unemployed, i.e., they stop looking for work. Therefore, traditional unemployment insurance would not be accessible to women in this situation. Many countries instituted temporary changes to their insurance systems during the crisis, such as expanding furlough pay and making unemployment benefits available also to those who stop working because of family obligations. Still, some of these policy changes were temporary and implementation varied across countries and U.S. states, so that some policy-induced asymmetries remain.

7.3 Wider Implications for the Future Labor Market

The pandemic recession will also have repercussions for the future of the labor market that far outlast the recession and the subsequent recovery. It is well known that losing employment during a recession is associated with persistent earnings losses for the affected workers (Stevens 1997, Davis and von Wachter 2011). The fact that more women than men were affected by employment losses will tend to increase the gender pay gap in the years after the recession. Women's higher flexibility of labor supply is also likely to result in persistent changes in labor force participation; some women (especially married women) who lost employment during the crisis will drop out of the labor force for an extended period or only return to part-time work. Hence, women's labor force participation will be lower as a result of the recession for years to come.

In addition to the direct impact on workers during the recession, the shock of the pandemic will also result in broader changes in the labor market that will shape the experience of current and future cohorts of workers alike. Arguably the most important one of these changes is increased employment flexibility, such as a much expanded ability to work from home for many workers. During the pandemic, most jobs that could be done from in principle were switched to being done from home in practice. Office workers who spend their days primarily working with computers almost universally worked from their living rooms, kitchens, and spare bedrooms during the pandemic, rapidly adopting new remote-work tools such as videoconferencing through Zoom in the process. Much of this change is likely to persist beyond the crisis. Employers and employees have paid the fixed cost of adopting remote work; learning-by-doing has taken place; employers have realized that working-from-home does not have to result in lower productivity; and employers have started to appreciate the savings from needing much less office space (Barrero, Bloom, and Davis 2021). Many have already announced that work-from-home will continue to be central to the post-pandemic work environment and have started the process of canceling leases for office space.

How is this new normal in the post-pandemic workplace going to change the labor market? Change is likely to occur in a number of dimensions, from commuting patterns and the commercial real estate market to new ways of fostering coherence and interaction in a workplace where face-to-face contact with coworkers is the exception rather than the norm.

For our purposes, the most interesting changes concern gender inequality in the labor market. We believe that increased work flexibility in the new normal has the potential to substantially reduce gender inequality. This expectation is based on two observations about the pre-pandemic labor market.

The first observation is that much gender inequality in the labor market in today's advanced economies is related to parenthood and childcare. The literature on the "motherhood penalty" establishes that gender wage gap are small among young workers who don't have children. In contrast, after having a child, the earnings of mothers stall, whereas fathers continue climbing the career ladder (e.g., Miller 2011; Adda, Dustmann, and Stevens 2017; Kleven, Landais, and Søgaard 2019; Kleven et al. 2019; Gallen 2018). These observations suggest that the unequal division of the burden of childcare between mothers and fathers is now the primary cause of gender gaps in the labor market.

The second observation is that job flexibility can do much to reduce inequality in the division of labor between spouses in terms of childcare and other home work. The general point that workplace flexibility is a particular benefit to women's careers has been advanced by Goldin and Katz (2011) and Goldin (2014). Regarding telecommuting specifically, Alon et al. (2020a) show that in pre-pandemic data, the ability to telecommute is strongly predictive of mothers' and fathers' engagement in childcare. For example, fathers who are able to work from home and are married to mothers who cannot, spend about 50 percent more hours on childcare compared to otherwise similar fathers who cannot telecommute.

Taken together, these observations suggest that the expansion of work flexibility brought about by the pandemic recession may substantially reduce gender inequality in the labor market in the long term, by allowing a more even division of childcare responsibilities among the now much larger share of couples who can both work from home, and by reducing the motherhood penalty that is at the root of today's gender inequality in the process. Our finding above that there were hardly any gender differences in the impact of the pandemic among workers who can telecommute is an indication of how powerful this channel can be.

While this justifies some optimism about gender equality in the future workplace, there is an important caveat. The evidence discussed in Section 6 suggests that among couples with children who both worked from home during the crisis, women continued to spend substantially more time on childcare, and their productivity likely suffered as a result. Even if the effects are not immediately visible, lower productivity at work will ultimately hinder career advancement and lower mothers' future earnings prospects. Albanesi and Olivetti (2009) show that expectations of an unequal division of labor in the household, once established, can be come self-fulfilling and create new barriers in the labor market. The implications of increased workplace flexibility for gender inequality are therefore closely linked to what happens to the division of labor inside the home.

Hence, the upshot is that the pandemic is likely to bring about changes in the post-pandemic workplace that open up the potential for much reduced gender inequality in the labor market. But for this potential to be realized, changes in the workplace are not enough; there also needs to be a shift in social norms and expectations that lead mothers and fathers to make more equal use of the added flexibility that the new workplace offered. Without such a shift, the strain of failing to do full justice to work, family, and self-maintenance needs that was shared by many workers during the pandemic will continue to be the reality of many working mothers in the new normal. Given these countervailing forces, evaluating the actual impact of expanded workplace flexibility on gender inequality in the post-pandemic labor market is an important task for future research.

8 Conclusions

In this paper, we have documented that in a large set of countries, the Covid-19 recession had a much larger impact on women's relative employment compared to pre-pandemic recessions. One cause of this disproportional impact on working women was the sectoral distribution of the recession, which fell heavily on service sectors with high female employment shares. Another cause was the increase in childcare needs during closures of schools and daycare centers, which had a bigger impact on mothers' versus fathers' labor supply. Yet, even when controlling for industry and occupation and considering only workers without children, in several countries we still find large remaining gender gaps, the causes of which are not yet well understood.

The fact that the pandemic recession was a shecession matters for the shape of the economic downturn and the recovery. Moreover, the pandemic recession is also likely to result in permanent changes in the labor market, such as a wider availability of work-from-home options and other forms of employment flexibility in the post-pandemic new normal. These changes are likely to result in persistent changes in women's and men's labor force participation and will shape gender inequalities in the labor market.

Beyond the employment of women and men, there are additional dimensions which make the pandemic recession of 2020 distinct from most others, and some of these dimensions are likely to interact with the issues considered here. One example is the impact of the pandemic on children's education. Early evidence suggests that virtual learning during school closures is often a poor substitute for in-person schooling and that children's skill acquisition will suffer as a result (e.g., Maldonado and De Witte 2020; Kuhfeld et al. 2020). Moreover, a growing literature suggests that school closures during the pandemic will widen educational inequality across richer and poorer families (Grewenig et al. 2020; Andrew et al. 2020b; Fuchs-Schündeln et al. 2020; Agostinelli et al. 2020; Jang and Yum 2020). If learning losses result in greater need for parental support in the following years, the impact on children can further amplify the persistent effect on women's employment documented here. Once again, the ability to work from home plays a central role, as parents who can work from home have an easier time supporting their children's learning (Agostinelli et al. 2020). Hence, lack of work flexibility likely had a double-negative effect on many families during the crisis, through the direct impact on employment and through the repercussions for children's education.

Another likely consequence of the pandemic is a sharp drop in fertility rates (Kearney and Levine 2020), which is already becoming evident in data on birth rates in late 2020 and early 2021. To some extent, the drop in fertility may reflect a delay in childbearing that will be compensated by higher fertility in subsequent years, leading to additional interactions with women's labor supply at that time.

Our analysis has also been limited to a set of high income countries. Many of the conditions that created a disproportionate impact on women's employment in this group are equally applicable to countries at other stages of development. For example, at the height of the Covid-19 pandemic schools closed in most countries of the world, making increased childcare needs during the crisis a near-universal phenomenon. Researchers have addressed how the optimal response to the pandemic in terms of health policy should be modified in developing countries (e.g., Alon et al. 2020c) but there is less work to date on implications for gender inequality in the labor market. Both the short-run impact on and the long-run repercussions for working women are likely to be different in developing countries compared to the group considered here, for example because of a bigger role of informal employment and much more limited remote-work opportunities. Addressing the impact of the global Covid-19 pandemic on the labor market for women and men in a broad set of countries is an important challenge for additional research on the crisis.

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Online Appendix

A Additional Tables and Figures

Table A1: Percent Living with Kids (0-14 years old) (2019)

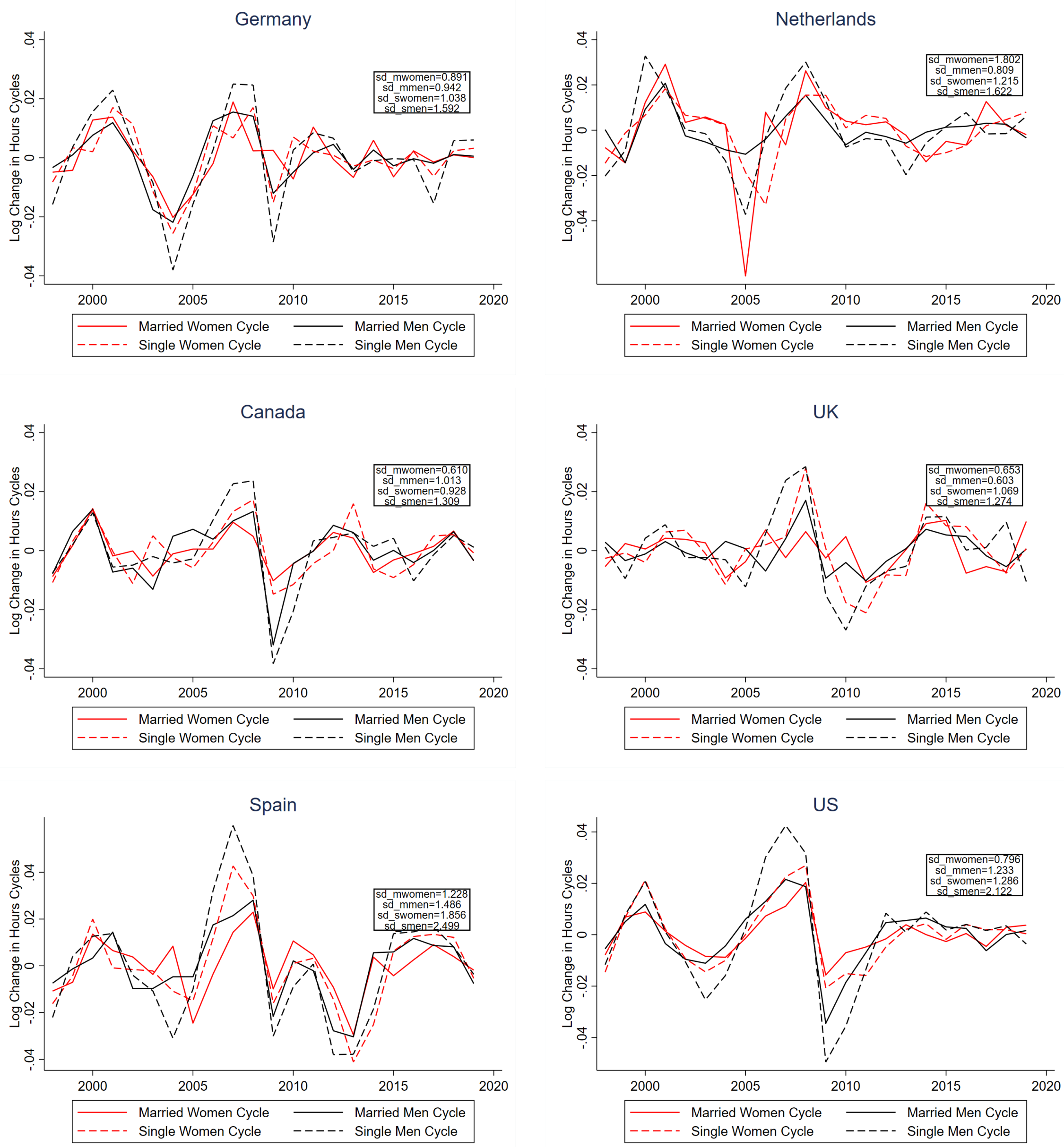
	Percent of all employed individuals (25-54)		
	living with kids	Mothers	Single mothers
Germany	37%	18%	3%
Spain	43%	19%	2%
Netherlands	44%	21%	3%
UK	47%	22%	5%
US	40%	22%	6%
Canada	33%	16%	2%

Table A2: Average Hours Worked Per Person (2019)

	Women					Men	
	Mothers				Non-mothers	Fathers (0-14)	Non-fathers
	(0-4)		(5-14)				
	Single	Couple	Single	Couple			
Germany	13	13	24	22	28	37	34
Spain	22	20	23	24	24	36	30
Netherlands	14	19	20	23	25	38	34
UK	12	17	22	25	30	39	36
US	23	21	29	26	29	39	34
Canada†	18	18	25	26	26	36	30

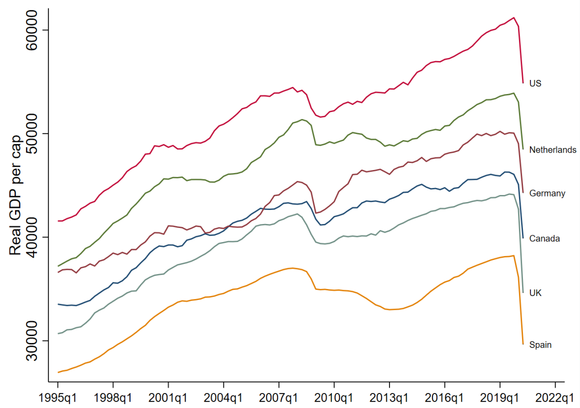
Notes: † Due to the limitation of data, the child groups are (0-6) and (6-12) for Canada instead of (0-4) and (5-14).

Figure A1: Cyclical Component of Hours Worked by Gender and Marital Status in Six Countries

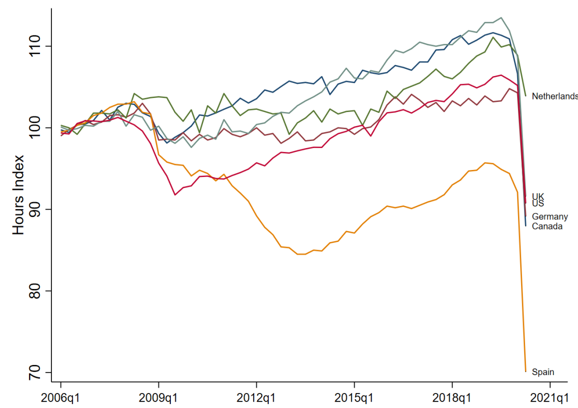


Notes: See Appendix B for data sources.

Figure A2: The Pandemic Recession in Six Countries

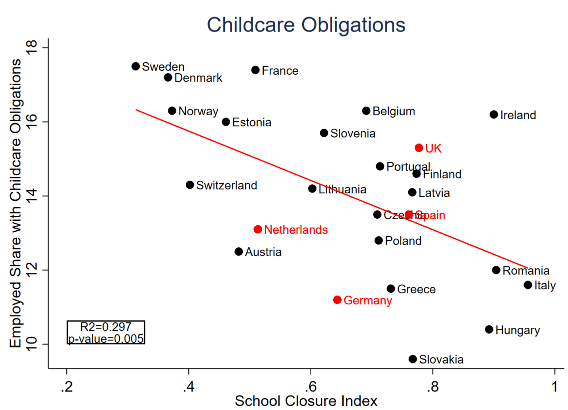


(a) GDP per capita

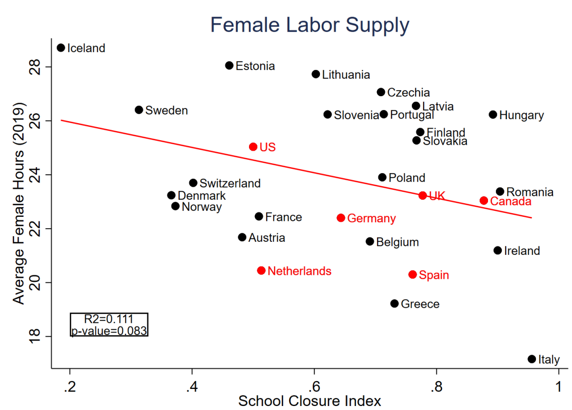


(b) Hours Worked

Figure A3: Correlation of Severity of School Closures with Childcare Obligations and Women's Labor Supply across Countries

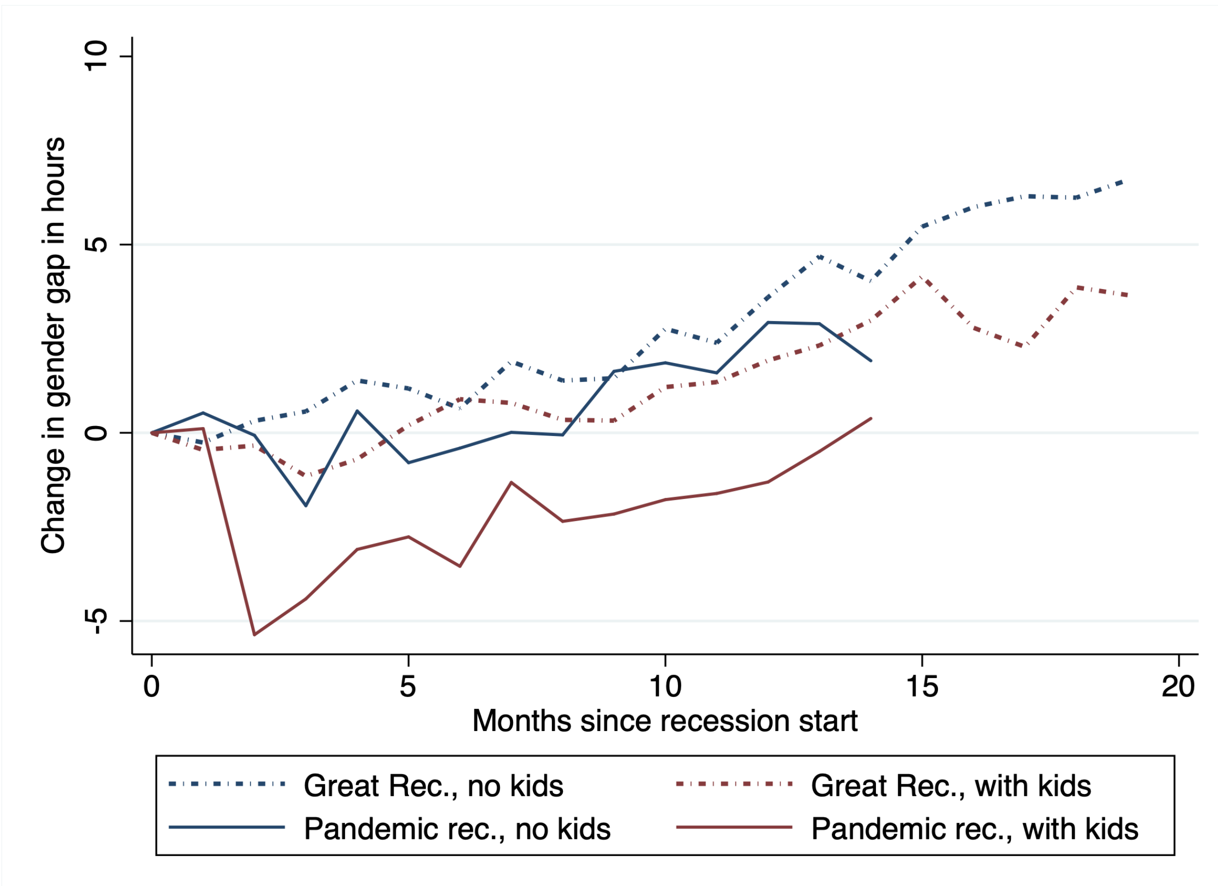


(a) Childcare Obligations



(b) Female Hours

Figure A4: Gender Gap in Hours during Great Recession and Pandemic Recession



Notes: Y-axis reports cumulative log point changes in the hours gender gap from the beginning of each recession. Hours series corresponds to seasonally adjusted hours worked last week. Sample includes all civilians ages 25 to 55 who are either employed, unemployed or NILF. Great Recession corresponds to Nov. 2007 - June 2009. Pandemic Recession corresponds to Feb 2020 - April 2021. Kid group are assigned based on age of own youngest child residing in the same household. Kids corresponds to those with school age children aged 0-17.

A.1 Regression Results: Education and Race, without Occupation/Industry Controls

Table A3: Pandemic-induced Changes in the Gender Gap in Employment by Education, **without** Occupation/Industry Controls

	USA	CAN	DEU	NLD	ESP	GBR
BA degree or higher (β_3)	-2.14	-0.39	-2.11	2.22	-0.91	-1.11
	(0.00)	(0.29)	(0.14)	(0.08)	(0.18)	(0.10)
pre-K kids ($\delta_{3,\text{pre-K}}$)	-0.56	3.08		3.76	-0.39	-0.16
	(0.47)	(0.00)		(0.09)	(0.75)	(0.89)
school age kids ($\delta_{3,\text{school}}$)	-5.08	-1.22	-2.14	1.28	-1.35	-1.45
	(0.00)	(0.04)	(0.31)	(0.45)	(0.12)	(0.13)
no kids ($\delta_{3,\text{none}}$)	-1.33	-1.61	-0.72	2.41	-1.03	-1.63
	(0.01)	(0.00)	(0.69)	(0.11)	(0.24)	(0.06)
Less than BA degree (β_3)	-2.19	-0.80	-0.80	0.91	-1.07	0.89
	(0.00)	(0.01)	(0.48)	(0.54)	(0.13)	(0.22)
pre-K kids ($\delta_{3,\text{pre-K}}$)	0.04	1.84		-2.48	0.76	1.76
	(0.96)	(0.00)		(0.49)	(0.59)	(0.20)
school age kids ($\delta_{3,\text{school}}$)	-3.87	-2.34	0.05	0.51	-2.46	-0.48
	(0.00)	(0.00)	(0.98)	(0.80)	(0.01)	(0.63)
no kids ($\delta_{3,\text{none}}$)	-2.23	-1.08	-1.27	1.80	-1.13	0.43
	(0.00)	(0.00)	(0.34)	(0.31)	(0.22)	(0.65)

Notes: The notes of Table 7 apply. For details on the data, see Appendix C.

Table A4: Pandemic-induced Changes in the Gender Gap in Hours by Education, **without** Occupation/Industry Controls

	USA	CAN	DEU	NLD	ESP	GBR
BA degree or higher (β_3)	-9.48	-6.95	-25.43	-19.46	-3.24	-7.44
	(0.00)	(0.00)	(0.09)	(0.11)	(0.35)	(0.06)
pre-K kids ($\delta_{3,\text{pre-K}}$)	-4.50	6.14		-69.68	0.44	-3.89
	(0.23)	(0.04)		(0.01)	(0.95)	(0.57)
school age kids ($\delta_{3,\text{school}}$)	-21.21	-7.48	-2.02	4.49	-6.91	-18.91
	(0.00)	(0.01)	(0.93)	(0.83)	(0.15)	(0.00)
no kids ($\delta_{3,\text{none}}$)	-5.81	-11.48	-45.25	-15.78	-2.70	-7.19
	(0.02)	(0.00)	(0.01)	(0.35)	(0.55)	(0.17)
Less than BA degree (β_3)	-8.80	-8.41	-26.07	5.18	-1.66	11.26
	(0.00)	(0.00)	(0.03)	(0.69)	(0.61)	(0.00)
pre-K kids ($\delta_{3,\text{pre-K}}$)	5.55	3.08		-56.74	18.87	24.32
	(0.15)	(0.24)		(0.21)	(0.00)	(0.00)
school age kids ($\delta_{3,\text{school}}$)	-16.52	-14.65	-23.36	-24.00	-3.23	2.84
	(0.00)	(0.00)	(0.25)	(0.30)	(0.47)	(0.59)
no kids ($\delta_{3,\text{none}}$)	-9.89	-8.49	-25.18	23.99	-7.55	7.33
	(0.00)	(0.00)	(0.09)	(0.16)	(0.07)	(0.13)

Notes: The notes of Table 8 apply. For details on the data, see Appendix C.

Table A5: Pandemic-induced Changes in the Gender Gap in Employment by Broad Race or Migration background, **without** Occupation/Industry Controls

	white / non-white		migration background			
	USA	GBR	CAN	DEU	NLD	ESP
Gender gap: whites / no migration (β_3)	-2.11	-0.36	-0.19	-0.53	2.03	-1.40
	(0.00)	(0.55)	(0.54)	(0.56)	(0.10)	(0.02)
pre-K kids ($\delta_{3,\text{pre-K}}$)	-0.83	0.70	1.65		4.45	-0.95
	(0.21)	(0.49)	(0.00)		(0.04)	(0.34)
school age kids ($\delta_{3,\text{school}}$)	-4.17	-1.25	-1.19	-0.19	1.41	-2.19
	(0.00)	(0.11)	(0.01)	(0.90)	(0.38)	(0.00)
no kids ($\delta_{3,\text{none}}$)	-1.75	-0.73	-0.47	-0.41	2.09	-1.32
	(0.00)	(0.33)	(0.18)	(0.71)	(0.15)	(0.06)
Gender gap: non-whites / migration (β_3)	-1.13	2.37	-1.09	-9.82	-0.27	0.96
	(0.07)	(0.07)	(0.01)	(0.01)	(0.89)	(0.44)
pre-K kids ($\delta_{3,\text{pre-K}}$)	3.37	3.15	3.96		-11.15	3.82
	(0.01)	(0.19)	(0.00)		(0.02)	(0.11)
school age kids ($\delta_{3,\text{school}}$)	-4.14	1.04	-2.90	-8.72	-1.42	-0.81
	(0.00)	(0.62)	(0.00)	(0.08)	(0.68)	(0.69)
no kids ($\delta_{3,\text{none}}$)	-0.96	1.34	-2.67	-9.59	1.98	-0.15
	(0.24)	(0.49)	(0.00)	(0.04)	(0.39)	(0.94)

Notes: The notes of Table 7 apply. For Canada, Germany, the Netherlands, and Spain, we group people by migration background instead of race. For details on the data, see Appendix C.

Table A6: Pandemic-induced Changes in the Gender Gap in Hours by Broad Race or Migration background, **without** Occupation/Industry Controls

	white / non-white		migration background			
	USA	GBR	CAN	DEU	NLD	ESP
Gender gap: whites / no migration (β_3)	-8.34	0.50	-7.49	-26.84	-3.60	-3.35
	(0.00)	(0.88)	(0.00)	(0.01)	(0.71)	(0.24)
pre-K kids ($\delta_{3,\text{pre-K}}$)	-0.48	9.91	1.80		-49.50	6.77
	(0.88)	(0.07)	(0.47)		(0.06)	(0.20)
school age kids ($\delta_{3,\text{school}}$)	-17.54	-11.55	-10.75	-16.45	-14.30	-5.08
	(0.00)	(0.01)	(0.00)	(0.31)	(0.39)	(0.16)
no kids ($\delta_{3,\text{none}}$)	-7.32	0.20	-7.88	-31.01	10.01	-5.41
	(0.00)	(0.96)	(0.00)	(0.01)	(0.46)	(0.12)
Gender gap: non-whites / migration (β_3)	-5.32	27.73	-3.95	-21.85	-16.88	5.29
	(0.06)	(0.00)	(0.04)	(0.55)	(0.42)	(0.35)
pre-K kids ($\delta_{3,\text{pre-K}}$)	12.36	26.80	12.74		-130.87	24.45
	(0.04)	(0.02)	(0.00)		(0.03)	(0.03)
school age kids ($\delta_{3,\text{school}}$)	-17.53	32.56	-11.28	-15.36	11.31	-0.67
	(0.00)	(0.00)	(0.00)	(0.75)	(0.79)	(0.94)
no kids ($\delta_{3,\text{none}}$)	-4.14	18.02	-7.50	-41.77	-7.50	-2.15
	(0.26)	(0.07)	(0.00)	(0.40)	(0.78)	(0.79)

Notes: The notes of Table 8 apply. For Canada, Germany, the Netherlands, and Spain, we group people by migration background instead of race. For details on the data, see Appendix C.

B Sources and Details on Cross-Country Data

The cross-country analysis is done based on various data sets, including micro data sets, aggregate data from national statistics (BLS, Statistics Canada), international organizations (Eurostat, OECD, World Bank) and indices constructed by external institutions or individual researchers. Table B7 gives an overview of the various data sets used. In Europe, harmonized micro data including all European countries are released with some delay. Thus we do not have access to the EU-LFS (on which we base our pre-pandemic analysis) for 2020 yet. Instead we use available aggregate statistics (from Eurostat) to analyze labor market impact of Covid-19 in the cross-country analysis. Whenever micro data is available (for earlier years, and for the US and Canada), we use the micro data instead. Since, we are restricted by the Eurostat aggregate tables for the post-Covid period, we harmonized the data from the US and Canada as close as possible to the indicators from the Eurostat aggregate tables. Further, Germany is largely missing from the 2020 Eurostat data due to delays in releasing basic labor market survey results because of data collection problems during the pandemic. To include Germany in our cross-country analysis, we made use of other available data sources (Mannheim Corona Study and IAB). However, using several data sources to create a complete time series has some shortcomings and hence we should put some caution in interpreting Germany in the cross-country analysis. The next section states which data are used in which figures/tables and for what purpose.

B.1 Data Sets used in the Cross-Country Analysis

	Tab1	Tab2	Tab3	Tab4	Tab5	Fig 1	Fig 3	Fig4	Fig5	Fig7	Fig6	FigA1	FigA2	TabA2-A1
Eurostat		x	x	x	x	x		x	x		x		x	
EU-LFS	x						x		x			x		x
WorldBank	x						x		x			x		
Ilostat		x	x	x	x	x		x	x					
CPS	x	x	x	x	x	x	x	x	x				x	
BLS										x	x			
MCS				x				x	x				x	
CLFS	x	x	x	x	x	x	x	x	x				x	
Stat Canada		x	x	x	x						x			
UNESCO		x	x	x	x									
Dingel and Neiman (2020)		x	x	x	x									
FRED						x			x	x	x			
OECD													x	
IAB		x		x		x		x	x				x	

Table B7: Dataset Map

B.1.1 EU-LFS Microdata Details

EU-LFS micro data is used to document cyclical properties of hours broken down by gender and marital status for 26 European countries. We restrict our analysis to 1998–2019 to include as many countries as possible. EU-LFS is not conducted at quarterly frequency before 2005 for many countries. As documented by Bick, Brüggemann, and Fuchs-Schündeln (2019), this creates inconsistency in both cross-country and time series comparison due to non-random sampling of reference weeks. We apply the same methodology and cleaning as Bick, Brüggemann, and Fuchs-Schündeln (2019) to overcome this issue. This methodology aims to correct for sampling of holiday weeks in accounting for "actual hours worked." Throughout our analysis, we use actual hours worked (hours worked in the reference week) variable. Only if an individual reports working less than usual in the reference week due to holidays, we replace it with use usual hours worked. When calculating average hours worked per gender/marital status, we include people who do not work as well (unemployed or not in the labor force) and we use sampling weights. We restrict our sample to individuals aged between 20-64. We construct our panel data set of 26 European countries (plus US and Canada) for 1998-2019 which includes the following variables: average hours worked and employment rate of men, women, married men, married women, unmarried men, unmarried women. The cyclicality analysis (Table 1) is done following the same strategy as in Doepke and Tertilt (2016). In Figure 3, we report the correlation between residual of HP filtered log relative hours (female/male) and residual of HP filtered real GDP for each country. HP filtering is done with a smoothing parameter of 6.25. In Figure 5, we run a regression of residual of HP filtered log relative (female/male) hours (employment) on the residual of HP filtered real GDP for each country. We calculate predicted relative hour (employment) change by multiplying the estimated β coefficient of that regression and observed change in real GDP between 2019Q4 and 2020Q2.[28]

Tables A1 and A2 are also based on EU-LFS data. Here we look at households, by identifying mothers and fathers and investigating their labor market characteristics for the selected 4 European countries that we are analyzing. We pursue the following strategy. EU-LFS provides information about the existence of children in the household, however in multigenerational families, existence of children is not enough to identify a women in the household as a mother. To do that we rely on some restrictions; the existence of chil-

[28]Given the number of observations per country (22 years), confidence intervals of β coefficients are somewhat large for some countries.

dren and either parent in the sample. We merge women (14+) with children (age 0-14) and men (14+) with children by using their person identifiers and mother/father identifiers. If a child matches with a women, we call her a mother, otherwise a non-mother. Hence, in order for us to identify a women as a mother, a child aged 0-14 should exist in the survey. The same applies to fathers as well. With this strategy, we cannot know if a woman is actually a mother when we do not observe the child in the sample. For divorced couples, we either cannot observe if a man is a father if he is not living with his children. We also call women/men who have children older than 14 as non-mother/non-father. In this part of the analysis, we restrict the sample to the individuals aged 25-54 and construct hours worked variable the same way we do above.

B.1.2 Details on Aggregate Statistics

Industry Tables:

We use the table called "Employment by sex, age and economic activity (from 2008 onwards, NACE Rev. 2) - 1 000 [lfsq_egan2] , age 15-64" to create Figure 6. We make adjustments to overcome the incompleteness of the data for certain country-industry-year observations and also to harmonize the data across Europe and the US. All the countries exist between 2008-present in quarterly data, except Switzerland where the quarterly data starts at 2010. We keep the data 2008-present for all countries but 2010-present for Switzerland. We remove mining and activities of extraterritorial organisations all together from all countries as they don't exist for many countries. Electricity, water, realestate, other services for Iceland, Estonia, Latvia, Greece, Lithaniua, Romania, Slovenia are incomplete for some countries and some quarters. If the total industry employment is missing for at most 2 consecutive periods, we replace it with the average of the previous period and one or two preceding periods. For some industries/countries in some years the employment by gender is missing. If so, we fill it in from other years. Even after these adjustments, water and realestate industries for Estonia and Iceland have too many missing observations. We remove water and realestate for Estonia and Iceland.

To establish a comparable industry coding with the US 1 digit BLS categories, we do the following aggregation:

trade_transportation_utilities=trade+transportation+electricity+water

business activities= professional + administrative services education_health=education+health

finance=finance+real estate

leisure=accommodation+arts

At the end, we have 11 industries: The five industries defined above plus the following six: public administration, construction, other services, information, manufacturing, agriculture. We apply seasonal adjustment method X-13ARIMA-SEATS by US Census Bureau to each of 11 industries for men and women separately. Finally total employment in each industry is calculated by summing up seasonally adjusted male and female employment.

We augment industry-gender employment statistics by including the US and Canada. For the US, BLS seasonally adjusted monthly gender-industry employment tables are used. BLS industry aggregation categories are taken as a reference to also harmonize the data across Europe versus the United States and Canada. In BLS categories, agriculture does not exist as an industry. We also exclude mining from the analysis as it does not exist for many of the European countries. For Canada, we use Statistics Canada industry-gender-employment tables. We apply X-13ARIMA-SEATS by Census Bureau seasonal adjustment method to 11 industry employment by gender.

Employment:

We use Eurostat "Total employment (in numbers) by gender, quarterly seasonally adjusted, age 20-64", to report post-Covid change in total employment. We augment Eurostat data by including the US and Canada from Ilostat: We use "employment by sex and age (thousands)" table for US and Canada, total employment for 20-64 at quarterly frequency.

Hours Index:

We use "Index of total hours worked in the main job by gender, quarterly seasonally adjusted, age 20-64" reported by Eurostat. We augment the Eurostat data by including the US and Canada. We estimate intensive margin hours worked from CPS and Canadian LFS and multiply that with total employment from Ilostat to end up with total hours worked. Since Germany is missing in the post-Covid period, we use data from the IAB's *Working Time Measurement Concept (Arbeitszeitrechnung)*, specifically the indicator "volume of work", which reflects the total hours worked by all employed people in social security jobs and self-employed, for 2019Q4 through 2020Q2. We scale it with the Hour Index from Eurostat by using the last available information for Germany (2019Q4). We use this data to calculate the evolution of total hours in 2020 in Germany. As IAB's gender break of the "volume of work" has not been available yet for 2020, we rely on the Mannheim Corona Study. To calculate the change in hours by gender between Q4/2019 and Q2/2020 in Germany, first, we estimate average hours by gender for July 2018 and Q2/2020 using the MCS. From this we can get the relative difference by gender between July 2018 and Q2/2020. Second, we use the hours index from Eurostat by gender from Q3/2018 to calculate the relative difference between the MCS results and the Eurostat hours index. Third, assuming that this relative difference is constant, we use it to normalise the MCS hours from Q2/2020 to match the level of the Eurostat hours index series. Fourth, we use the Q4/2019 Eurostat data and the normalised MCS hours from Q2/2020 to calculate the reported change in hours by gender. Fifth, we calculate the difference in scale between the change in average hours in MCS and in IAB data, (MCS data overestimates the change due to a different concept of hours). Then, we recalculate hours indices by gender by scaling the changes using the difference in change between MCS and IAB.

B.2 Figure and Table Notes

1. Figure 1: The Pandemic Recession in Seven Countries

    - European countries: Eurostat quarterly seasonally adjusted Hours Index (20-64) and "Chain linked volumes (2010), million euro, quarterly, unadjusted data (i.e. neither seasonally adjusted nor calendar adjusted data), Gross domestic product at market prices" provided by Eurostat and then seasonally adjust it ourselves (using X-13ARIMA-SEATS by the Census Bureau).
    - US and Canada: We use Real Gross Domestic Product, Billions of Chained 2012 Dollars, Quarterly, Seasonally Adjusted Annual Rate for the US and Gross Domestic Product by Expenditure in Constant Prices: Total Gross Domestic Product for Canada, National Currency, Quarterly, Seasonally Adjusted from FRED . Current Population Survey, Canadian Labor Force Survey and Ilostat employment estimates (age 20-64) are used to calculate total hours index (section B.1.2 for more details).
    - We report cyclical component of HP filtered (smoothing parameter 1600) seasonally adjusted series.

2. Figure 3: In Most Countries, Women's Relative Labor Supply was Countercyclical Before 2020

   - European countries: EU-LFS annual micro data is used to calculate average actual hours worked in 26 European countries.
   - US and Canada: Current Population Survey and Canadian Labor Force Survey to calculate average hours for all people aged 20-64.
   - We use annual GDP (constant 2010 US$) from WorldBank Development Indicators for the pre-Covid cyclicality analysis. The data code is NY.GDP.MKTP.KD.

3. Table 1: Volatility of Hours Worked, by Gender and Marital Status, 1998-2019

   - European countries: EU-LFS annual micro data is used to calculate average actual hours worked.
   - US and Canada: Current Population Survey and Canadian Labor Force Survey to calculate average hours for all people aged 20-64.

4. Figure 4: Post-Covid Change in relative female/male Labor Supply

   - European countries: Eurostat seasonally adjusted employment by gender (age 20-64), seasonally adjusted Hours Index by gender (20-64). We augment the data by using MCS and IAB to include Germany (see section B.1.2.)
   - US and Canada: Current Population Survey and Canadian Labor Force Survey and Ilostat employment estimates (age 20-64) to calculate total hours index (see B.1.2 for details.)

5. Figure 5: Predicted versus Observed Change in relative Labor Supply

   - Observed changes: For European countries, Eurostat seasonally adjusted employment by gender (age 20-64), seasonally adjusted Hours Index by gender (20-64). For the US and Canada Current Population Survey, Canadian Labor Force and Ilostat employment estimates (see B.1.2 for details.)
   - Predicted changes: EU-LFS and Current Population Survey and Canadian Labor Force Survey

6. Figure 7: Employment Decline across Sectors, United States

- BLS monthly industry employment statistics have been converted to quarterly frequency to be consistent with the European frequency for the rest of the analysis. Mining is excluded.

7. Figure 6: Female versus Male Industries

   - Gender classification is done comparing within industry female share to overall female share in the aggregate employment within each country. If within industry female share is higher (lower) than overall female share in employment in an industry for all countries, that industry is classified as female (male). The industries for which within industry share is close to overall female share (slightly higher or lower depending on the country) are classified as neutral industries. Further details on constructing above 11 main industries out of 21 industries from EU NACE classification to be compatible with BLS NAICS main industry coding are in the section B.1.2.

     Based on this process, we end up with the following male industries: construction, manufacturing, agriculture, and information (agriculture is excluded in the US). Neutral industries are trade, transportation, utilities, public administration, finance, business and administrative activities. Female industries are education, health, leisure and hospitality and other services.

   - We apply X-13-ARIMA-SEATS seasonal adjustment method by Census Bureau to Eurostat industry-gender quarterly employment statistics for the period (2008q1-2020q2). The aggregates are calculated out of seasonally adjusted gender-industry groups.

8. Regression Tables 2, 3, 4, 5

   - Teleworkable fraction is taken from Dingel and Neiman (2020). The share of hospitality, leisure and other services is calculated from Eurostat industry employment tables, BLS and Statistics Canada for the year 2019. Female hours is the average female hours (including int/ext margin) for the age-group 20-64 in year 2019 calculated from EU-LFS, CPS and Canadian LFS. School closure index is calculated from UNESCO, Covid-19 education response, as the fraction of days where schools were not fully open between March and June 30th out of all school days (excluding academic breaks), where partially closed days are weighted by 1/2. The data source is:

     https://en.unesco.org/covid19/educationresponse.

9. Table 6: Policies and Labor Market Structure Across Six Countries

   - Teleworkable fraction, the share of hospitality, female hours and school closure index are the same as in Tables 2, 3, 4, 5. Employment protection index is from OECD Employment Protection Legislation Database, 2020 edition. Pre-covid cyclicality of relative hours is the same as in Figure 3.

10. Table A1 and A2: Percent Living with Kids (0-14 years old) (2019) and Average Hours Worked Per Person (2019)

    - We use EU-LFS micro data for European countries, CPS and Canadian LFS for the US and Canada.

11. Figure A1: Cyclical Component of Hours Worked by Gender and Marital status

    - We use EU-LFS micro data for European countries, CPS and Canadian LFS for the US and Canada. We apply HP filter with smoothing parameter 6.25 to average hours worked broken down by gender and marital status and report cyclical component.

12. Figure A2: The Pandemic Recession in Seven Countries

    - OECD GDP per capita; "Gross domestic product - expenditure approach HVPVOBARSA: Per Head, US dollars, volume estimates, fixed PPPs, OECD reference year, seasonally adjusted"
    - Eurostat; the index of total hours worked (20-64) which is augmented by CPS, Canadian LFS, Ilostat and IAB to include Germany, US and Canada (see section B.1.2 for more details.) We report the raw hours index.

13. Figure A3: School Closure

    - Employed share with childcare obligations is taken from (Fuchs-Schündeln, Kuhn, and Tertilt 2020) (third column of Table A1 in the paper). Average female hours per person is estimated using EU-LFS, CPS and Canadian LFS.

C Details and Sources for the Micro Data

Table C8 gives an overview of the micro data we use. As the table shows, there is large heterogeneity in sample size across countries due to the different kinds of surveys we use. The table also includes basic summary statistics of the population we use. The remainder of this section describes details of the data used for each country.

Table C8: Sample Population Characteristics

	USA	CAN	DEU	NLD	ESP	GBR
Labor Supply						
percent employed	78	81	85	82	74	85
hours worked last week	30	27	31	25	24	27
percent telecommuting	39			63		14
Percent Female	51	50	51	56	50	51
Percent Married	57	50	56	74	52	54
Percent Single Mothers (0-17)	7	4	2	3	3	5
Percent with Children			41			
pre-kindergarden (0-5)	17	21		13	16	21
school age (6-17)	28	26		29	32	30
Percent Non-white/Immigrant	25	29	9	23	19	15
Percent College Graduate	41	37	39	48	43	40
Sample Size	919,296	917,951	38,687	50,491	421,621	215,589

Notes: Sample includes the civilian population, ages 25 to 55, from Jan 2019 - Sept 2020. In the USA, telecommuting includes all those working remotely, at any point in our sample, because of COVID-19. Child age brackets are assigned by the age of the youngest child (<5 and 5-17). In the Netherlands, telecommuting is defined as working at least one hour from home in the reference week and "Percent married" are defined as cohabiting or married. Due to data limitations, for Germany we can only calculate the share individuals having children below 16 (including pre-K) and hours worked last week include commuting time (and partly studying). In Spain, the definition of "College Graduate" includes individuals with advanced vocational training, specific and equivalent, plastic arts and design, and sports education.

C.1 Micro Data from the United States

Data for analysis of the United States is drawn from the basic monthly files of the Current Population Survey (CPS), retrieved from IPUMS-CPS at the University of Minnesota (www.ipums.org). The CPS is a household-level survey maintained by the U.S. Bureau of Labor Statistics (BLS) which gathers information on roughly 60 thousand households in a reference week containing the 12th day of each month. Each household appears in the CPS for a total of eight months and records can be longitudinally linked to provide a panel dimension to the data. Specifically, respondents are included for four consecutive months, omitted for eight months, and then interviewed for an additional four consecutive months. Using the BLS provided population weights, the data are representative of the adult (16+) civilian non-institutional population.

Unless otherwise noted, the main sample corresponds to the working-age population, ages 25 to 55, not in the military. For this sample, the core CPS files provide data on demographics (age, race, and ethnicity), education, marital status, industry, occupation, employment, and hours worked. Industry and occupation categories are combined into 500 work-type categories used in the analysis. The CPS also provides data on the presence and age of the respondent's own children living in the household. We use this data on children to classify households by the presence of children ages 0-17, identified by age of the youngest child. At times we also differentiated between pre-K children under 5 and school age children ages 5-17.

Data on telecommuting status come from the CPS COVID-19 Supplement which added a battery of five questions to the CPS basic monthly survey beginning in May 2020 to measure the impact of the COVID-19 pandemic on the labor force. Specifically, the supplement provides data on whether employed respondents teleworked or worked from home for pay at any time during the previous four weeks due to the COVID-19 pandemic. To conduct the regression analysis using telecommuting variables, we exploit the panel dimension of the CPS to identify pre-pandemic labor market outcomes for those who could and couldn't telecommute during the COVID-19 recession.

C.2 Micro Data from Canada

Data for analysis of Canada is drawn from the monthly files of the Labour Force Survey (LFS), retrieved from Statistical Information Service of Statistics Canada. The LFS is a household-level survey carried out monthly by Statistics Canada, which obtains information on approximately 56 thousand households usually in the week containing the 15th day of the month.[29] The LFS uses a rotating sample. Each month, one-sixth of the households are newly selected and kept for six consecutive months. All selected civilian household members who are aged 15 and over are interviewed for labour force information. The LFS data are used to calculate the official unemployment rate and other labour market indicators.

Unless otherwise noted, the main sample corresponds to the working-age population, ages 25 to 55. For this sample, the LFS files provide data on demographics (age, migration status), education, marital status, industry, occupation, employment, and hours

[29]Note that we do not have the household identifier and only cross-sectional analysis is conducted.

worked. 21 Industry and 40 occupation categories are combined into 840 work-type categories used in the analysis.[30] The LFS also includes information about the family such as the age of the children living in the household. We use this data on children to classify households by the presence of children ages 0-17, identified by age of the youngest child. At times we also differentiated between pre-K children under 6 and school age children ages 6-17.

In Canada, we set the pandemic indicator D_t to one starting in March 2020 (one month earlier than in the other countries). We do this because monthly data is available and the negative employment effect of the pandemic is apparent in Canada already in March.

The LFS distinguishes between married and living in common-law for the marital status. For the regressions with marital status included as controls, we classify all respondents who are married legally as married. In particular, respondents who are living in common-law are considered as not married. In the single mothers analysis, we define single mothers as mothers who are neither married nor living in common-law.

Finally, we define immigrants as everyone born outside of Canada.

C.3 Micro Data from Germany

The micro data analysis on Germany links two slightly different types of surveys, the German Internet Panel (GIP) and the Mannheim Corona Study (MCS). The GIP is a longitudinal data set based on a random probability sample of the general population in Germany aged 16 to 75. The survey is conducted bimonthly and operated by the Collaborative Research Centre 884 at the University of Mannheim.[31] Interview days are usually spread out over an entire month and we rely on information from waves 36, 37, 39, 43, 45, 47, and 49 (corresponding to 07/2018, 09/2018, 01/2019, 09/2019, 01/2020, 05/2020 and 09/2020). The monthly sample size is between 4,400 and 5,400.[32] During the pandemic, participants of the GIP were interviewed for a special Covid survey,

[30] For the unemployed or the NILF who were employed before, LFS still contains their prior industry and occupation information. We created an additional occupation and industry for the individuals with missing occupation and industry information in any regressions that have work-type controls.

[31] A description of the GIP can be found in Blom, Gathmann, and Krieger (2015). For additional information see www.uni-mannheim.de/en/gip/for-data-users/. The CRC 884 was funded by the Germany Research Foundation, grant number 139943784.

[32] The sample size of wave 36 (July 2018) is approximately 2,400. Subsequently, the GIP has been supplemented with additional participants later in 2018.

the Mannheim Corona Study (MCS).[33] Between March 20 and July 10, every week approximately 3,600 interviews were conducted with reference days being spread equally within each week. We were able to get early access to the data onsite at the University of Mannheim.[34]

For the micro data analysis, we combine the information of the GIP with the MCS and do not condition our sample to be balanced as we rely on its cross-sectional properties. We are not using weights in the regressions because the data does not contain consistent weights over the entire time period. Non-response rates of the GIP and the MCS differ slightly which might lead to artificial changes over time. By including controls into our estimations, we intend to take care of this.

As most post-pandemic observations lie between March 20 and July 10 and hence in the second quarter of 2020, our estimates for pandemic induced changes in Germany average over a different time period than the estimates for the other countries (esp. USA, Canada, Spain, UK). This might affect the magnitude of the coefficients as the crisis had probably a more severe impact during the month of April, May and June. Hence, the estimated coefficients for Germany are not perfectly comparable across countries.

Due to data protection, age is made available only in birth year brackets. We restrict our sample throughout the micro data analysis to include individuals born between 1965 and 1994, i.e., those individuals were between 25 and 55 in 2020. Information on marital status, German citizenship, and highest achieved education is collected in each September wave.[35] We define migration background as having no German citizenship or being born outside of Germany, which is only asked in wave 47.

We use information on the employment status from the GIP waves which is available in January 2019, September 2019, January 2020 and September 2020. We define the former three waves as pre-pandemic. In addition, we use information from all MCS waves and define them together with the September 2020 wave from the GIP as post-pandemic observations. Employment is consistently defined as being full-time employed, part-time employed or being in marginal employment, i.e., having a so called "mini-job"

[33]A description of the MCS data can be found in Blom et al. (2020). For more details on the MCS see www.uni-mannheim.de/en/gip/corona-study/. The MCS was partly funded by the Network for Interdisciplinary Social Policy Research, German Federal Ministry of Labour and Social Affairs (grant number: FIS.00.00185.20).

[34]The data can be accessed via GESIS www.gesis.org/en/home.

[35]We define three education groups: (i) no school degree or any school degree, (ii) some college or vocational training or equivalent, and (iii) university degree or equivalent.

(450-Euro job). During the pandemic, employees who are furloughed or in short-term work or work from home are defined as employed.

The available measure of hours worked comprises hours worked in the main and second job, but also time spent on commuting and studying on a regular work day in the reference week. We assign zero hours to all non-employed, thereby we avoid to include the hours of those who study but do not work. The only available pre-pandemic information on hours dates back to wave 36 in July 2018. During pandemic times, the exact same question has been asked in the following eight weeks: April 17-23, May 22-28, May 29-June 4, June 5-11, June 12-18, June 19-25, June 26-July 2, July 3-10. Hence, two caveats need to be noted: first, all pandemic-induced changes in hours are relative to July 2018 without including time trends. Second, since commuting clearly declined due to the pandemic, some of the estimated decline in hours is caused by the commuting decline.

The GIP data only records industry information for every survey participant in each September wave. The data covers 19 different industries. Unfortunately, information on occupation is not available. In each GIP and MCS waves besides the September waves, we assign each individual its (closest) past industry indicator. In case this information is not available, we rely on industry information from observations in later waves. To those observations for which no industry information is available, we assign an artificial industry category to preserve those observations.[36] Hence, we use 20 work type categories in the analyses of the German data.

We construct information on the presence of children below 16 in the household from various survey waves. Due to data limitations, we could define more detailed age categories only for a considerably smaller subset of our sample. First, in each September wave information on four other members of the household is recorded including the age bracket of each member (e.g., <16 years). Second, in each wave of the MCS, we know if a child below 16 lives in the household or not. Third, in May 2020 respondents of the GIP were asked to provide the birth history of the children in their household. Relying on these information, we are able to create an indicator for a child below 16 living in the household for earlier waves as well. We then use the longitudinal structure of the data and infer for missing child information the likely current status from the close past or future.

[36] They only account for a bit more than 2% of the sample.

To construct the variable of cohabitation, we follow a similar approach as for children in the household: we first rely on the information on other household members in each September wave and enrich it with information on living with a partner collected in three MCS waves. We then also use the longitudinal dimension to extrapolate those characteristics from the close past or future.

Due to the above described data limitations and the shorter time series, we neither include gender specific linear time trends nor control for seasonal effects or for the interaction between summer months and working in the education sector.

In Table C9 we summarize the number of observations in each regression for the Germany.

Table C9: Number of observations in gender gap regressions, Germany

Regressions	Baseline, education, race		Single mothers	
	Employment	Hours	Employment	Hours
Observations	37,596	14,923	8,129	3,232

Notes: Column 1 refers to Tables 7, 11, 13, A3, A5. Column 2 refers to Tables 8, 12, 14, A4, A6. Column 3 and 4 refer to Table 15. Note that for the overall impact in Tables 7 and 8 we do not condition on controls and therefore its sample size is slightly higher.

C.4 Micro Data from the Netherlands

The LISS panel (Longitudinal Internet studies for the Social Sciences) consists of 5,000 households living in the Netherlands, comprising approximately 7,500 individuals of all ages, and 4,000 individuals between 25 and 55. Households are representative of the Dutch population as the panel is based on a true probability sample of households drawn from the population register by Statistics Netherlands. Panel members complete online questionnaires every month and are paid for each completed questionnaire. In addition to the LISS Core Study, any researcher or policy maker can create and add a module to collect data for research purposes.

The main sample used for analysis consists of the working-age population, aged 25 to 55. The variables used for this analysis come from different modules of the LISS data. Employment rates and all individual characteristics such as age, gender, migration background, number of children or marital status come from the Background module which is updated every month by one of the household member. Usual hours worked as well as occupation and industry come from the Work and Schooling module, which is part of the LISS Core Study, and is answered by a random half of the panel every year. Actual hours come from the Effects of the Outbreak of Covid-19 modules wave 1 to 5 which have been collected in March, April, May, June and September 2020 by the CoVID-19 Impact Lab (von Gaudecker et al. 2021). Finally information on the number of hours worked while watching kids comes from the Time Use and Consumption module wave 7 which has been collected in April 2020 by the CoVID-19 Impact Lab as well (von Gaudecker et al. 2021). We are grateful for the financial support of the CRC-TR 224 (funded by the Germany Research Foundation) for the data collection of these two modules. These last two modules have been answered by a random half of the panel each month of data collection.

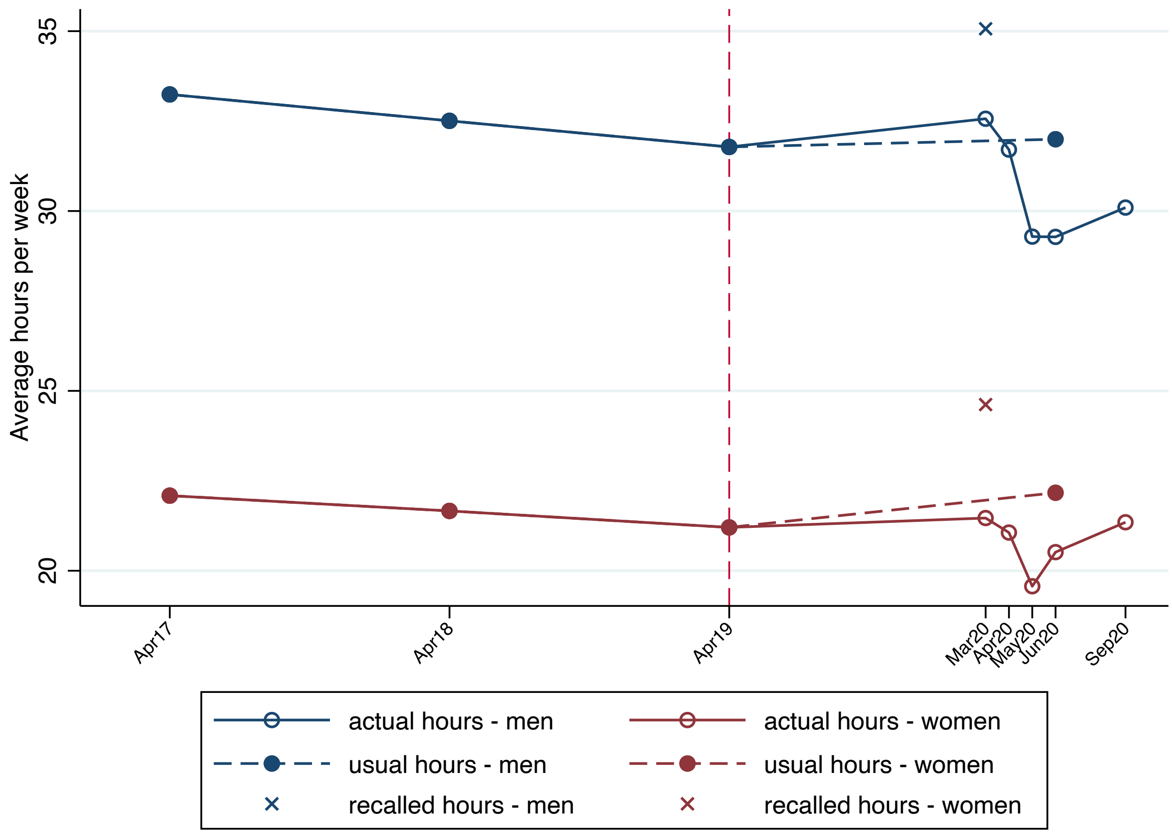
Figure C5 illustrates that the exact phrasing of the question on hours worked is important. In particular comparing questions about hours worked per week with a recall question on the past does not seem to work well as Figure C5 shows quite clearly. A measure of hours worked based on recalling the past is clearly upward biased[37], so by using it we would overestimate the pandemic-induced decline. We thus exclude hours worked based on the recall question in our analysis and use the question "How many hours per week do you work on average?" pre-pandemic and "On average, how man hours did you work in the past seven days?" since the pandemic started. To be precise, during the pandemic, the survey asked about home and on-site hours separately, we add them up to construct our measure of total work hours.

For the regressions, to have consistency over time, we also exclude the "usual hours" question in June 2020. Note that in this month we have answers to two different hours questions. As the figure shows the average answer to the "usual hours" question is well above the number obtained from the question on actual hours in the last seven days. The latter should better capture the reality during the pandemic, while people likely interpret "usual hours" to be related to pre-pandemic hours. Finally, we also exclude March in the regressions (both in the hours and employment regressions), because while for the other countries we consider March a pre-pandemic month, in the LISS data the questions were asked after the first lockdown measures were implemented. At the same time, one would not expect affects on the economy to materialize within a week or so,

[37]The mid-March survey includes the question "How many hours per week did you work on average at your workplace and from home in early March (or before the coronavirus affected your work)? And in the past seven days?" As the figure shows, the answer to this question is well above the historical average.

thus we chose to exclude it. Yet, including it as a post-pandemic month does not change our results much.

Figure C5: Hours Worked in the Netherlands, comparing different questions



Notes: This graph represents the average hours of respondents between 25 and 55 years old by sex. Plain dots are average usual hours, empty circular dots are average hours of the last week, and crosses are recall hours in a week before the pandemic.

Employment rates come from the Background module in which respondents are asked to specify their current employment status. The set of responses for this question doesn't allow us to distinguish a furloughed worker from a non-furloughed worker, and we count a furloughed worker as an employed person. The marital status dummy variable is combination of the cohabitation variable and the marital status variable in the limited sense. This dummy is equal to one if the individual is either married or cohabiting with someone else. In the Netherlands, about 40% of cohabiting couples are not married. Occupation and industry variables are filled every year by a random half of the panel in the Work and Study module. The occupation and industry of each working age individual is inferred using past studies up to 2016.[38] For a given individual, only the most recent information on occupation and industry is considered. Industry and occupation categories are combined into 124 work-type categories used in the analysis.[39] To construct the migration background dummy variable, we use the variable "origin" from the background module which can take five values ("Dutch background," "First generation foreign, Western background," "First generation foreign, non-western background," "Second generation foreign, Western background," and "Second generation foreign, non-western"). We set this dummy variable equal to one if the individual has an origin different from "Dutch background." The Effects of the Outbreak of Covid-19 modules contain information on hours worked at home and on-site. We use these variables to construct the telecommuting variable. An individual is able to telecommute if she has been working from home at any point between March and September 2020. In addition to the hours worked at home and on-site, in the Time Use and Consumption module wave 7, respondents are asked about the time spent in the last seven days doing "paid work at home while at the same time I am also responsible for the care of one or more children." We use these three variables to calculate the fraction of hours worked at home or not, while looking over the children.

C.5 Micro Data from Spain

Data used for the analysis of the Spanish labor market is drawn from the Economically Active Population Survey (EAPS), provided by the Spanish National Statistics Office (https://ine.es/en). The survey collects quarterly data on roughly 60,000 households. Once selected, the same household is interviewed for six consecutive quarters, and replaced with a newly drawn household thereafter.[40]

The main sample used for analysis consists of the working-age population, ages 25 to 54, who are not part of the military.[41] For this group of individuals, the EAPS provides information on socio-demographic characteristics such as age, migration background, education, and marital and cohabitation status, as well as employment, industry, occupation, and hours worked. In our analysis, we define hours worked as the sum of hours

[38]The most recent module we consider is April 2019.

[39]For the individuals who were unemployed or not in the labor force from 2016 to 2019, the information on occupation and industry can be missing. We created an additional synthetic occupation and industry category for those missing cases.

[40]Note that the data set used in this context is a cross-sectional version, providing a rich set of covariates, but no longitudinal identifiers.

[41]Due to age categories (50–54 and 55–59) available in the data, individuals aged 55 years are excluded from the sample in the case of Spain.

worked in both primary and secondary occupation. Employment and industries are summarized into ten broad categories each.[42] For the analysis, we combine occupation and industry into work-type categories.[43] The main regressions also include a summer-education dummy to control for seasonal drops in hours worked related to teachers on vacation. Due to the broad definition of industries, this indicator includes individuals working in public administration, education, and healthcare operations in the Spanish context.

The EAPS also provides data on the children living in each of the interviewed households. We use the age of the youngest own child to define whether an individual has children under 5 or school age children.[44] We use the seven education categories provided by EAPS to define three broad education groups. In the definition of college vs. non-college individuals, the group of college graduates also includes individuals with advanced vocational training, specific and equivalent, plastic arts and design, and sports degrees. Finally, we make use of EAPS information on the nationality and birth country of respondents. Specifically, we define Spanish nationals who are born in Spain as individuals without migration background and individuals with foreign nationality as well as Spanish nationals born outside Spain as individuals with migration background.

C.6 Micro Data from the United Kingdom

For our analysis of the United Kingdom, we rely on the UK Labour Force Survey which is a quarterly household survey.[45] The survey follows households for five quarters and interviews are conducted every thirteen weeks. Interview dates and reference weeks are spread out equally over the course of the quarter. We use the repeated cross-sections of the individual-level Quarterly Labour Force Survey (QLFS) between Q1/2019 and

[42] In the definition of employment, we follow the categorization used in the official data documentation of the EAPS. We define individuals to be employed if they worked during the previous week; if they were absent due to vacations, birth of child, or illness; if they were absent for other reasons and will be back to work in no more than three months or were paid 50% or more of their regular salary; if they did unpaid work in a family business; and if they were absent from work and they are entrepreneurs, independent workers or members of a cooperative.

[43] Together with two additional categories when industry or occupation are missing, and given that some combinations of occupation and industry have no observations, we get a total of 90 work-type categories with positive entries.

[44] Note that EAPS does not provide information on age in years, but only groups children into the following relevant age ranges: 0–4, 5–9, 10–15, and 16–19 years. In the case of Spain, children between 5 and 19 years are therefore included in the group of school age children.

[45] The data can be accessed via the data distribution platform 'UK Data Services' (https://www.ukdataservice.ac.uk/).

Q3/2020 which contain approximately 30,000 individuals per quarter and are representative for the British population using appropriate weights provided by the Office for National Statistics (ONS). An updated weighting procedure provided by the ONS tackles the smaller achieved sample size and a potential sample bias during the first weeks of the Covid-19 crisis in 2020 (Office for National Statistics 2020). We use the provided weights in all regressions and descriptive outputs.

The sample is restricted to working-age population, i.e., 25 to 55, and to those not working in the military. The data contains information on demographics of the observed individual (e.g., age, race/ethnicity), on the age of the youngest child below 19 in the family, on marital status, on cohabitation, and on the highest attained education. In addition, we use work-related data on employment, hours worked last week as well as industry and occupation.

In our analysis, we rely on the employment definition of the ONS and the Labour Force Survey. We define employment as (i) having done paid work in the reference week or if not, being temporarily away from job/paid work, as (ii) doing unpaid work in own business or in the family business, or as (iii) being on a government training scheme and working for an employer. The last two groups are small, e.g., they add up to 0.32% of the sample in Q3/2020, and results are robust to dropping those individuals. Using this employment definition implies that furloughed workers but also those on holidays are considered to be employed. To create the hours variable that includes the extensive and intensive margin, we rely on the measure "actual hours worked last week in all jobs" and assign it to all employed individuals while the hours of non-employed are zero.

We classify occupations using the two-digit categories in the Standard Occupational Classification 2010 (25 categories). Industries are defined at the one-digit level corresponding to the Standard Industrial Classification 2007 (19 categories). In the assignment of the occupation and the industry, we first rely on information from the current job. If this is unavailable, which is the case for all non-employed, we use information from the previous job. If information about industry and occupation are non-missing, we combine both to construct work type categories which are used as "occupation$\times$industry controls" in the regressions. If either no occupation or no industry can be assigned to non-employed individuals, we group them in an additional category. In total, this approach yields 476 different work types.

We define four education levels: (i) less than General Certificate of Education (GCE) A-level, (ii) GCE A-level or equivalent, (iii) some college or vocational training or equivalent (iv) university degree (BA or more) or equivalent. Race is defined as white or non-white. In addition to education, race, and marital status, we use age brackets as controls in our regressions (25-29, 30-34, ...).

In the telecommuting analysis, we rely on a question regarding "whether the individual is working from home in the main job." This question is answered by everybody who is employed, also those who are temporarily away from the job, i.e., those who worked zero hours in the reference week. We assign a telecommuting status if the respondent replies with (i) "in own home," (ii) "in the same grounds or buildings as home," or (iii) "in different places using home as a base" and a non-telecommuting status if (iv) working "somewhere quite separate from home." The advantage of this variable is that it is already available in all cross-sections before the pandemic. According to our definition, the total share of telecommuting was 13.6% in Q1/2020, 16.4% in Q2/2020, and 17.3% in Q3/2020. We can then estimate the differential changes in the gender gap in hours worked of employed conditional on telecommuting status as we are able to control for the average telecommuting status of different groups before the start of the pandemic.

In Table C10 we summarize the number of observations in each regression for the UK.

Table C10: Number of observations in gender gap regressions, UK

Regressions	Baseline, education, race		Single mothers		Telecommuting
	Employment	Hours	Employment	Hours	
Observations	211,945	209,813	65,126	64,759	177,426

Notes: Column 1 refers to Tables 7, 11, 13, A3, A5. Column 2 refers to Tables 8, 12, 14, A4, A6. Column 3 and 4 refers to Table 15. Column 5 refer to Tables 16 and 18. Note that for the overall impact in Tables 7 and 8 we do not condition on controls and therefore its sample size is slightly higher.

D Decomposition of Pandemic-Induced Changes in the Gender Gap

Recall our empirical model of labor supply in equation (4),

$$y_{it} = \boldsymbol{\theta}_0\,\mathbf{Kid}_{it} + \boldsymbol{\theta}_1\,\mathrm{F}_i \times \mathbf{Kid}_{it} + \boldsymbol{\theta}_2\,\mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\theta}_3\,\mathrm{F}_i \times \mathbf{Kid}_{it} \times \mathrm{D}_t + \boldsymbol{\theta}_4\,\mathbf{Job}_{it} + \boldsymbol{\theta}_5\,\mathbf{Job}_{it} \times \mathrm{D}_t + \boldsymbol{\theta}_6\,\mathbf{X}_{it} + \epsilon_{it}. \quad (7)$$

The pandemic-induced change in labor supply is,

$$\frac{\partial y_{it}}{\partial D_t} \equiv \mathbb{E}\left(y_{it} \mid D_t = 1, \mathbf{Kid}_{it}, \mathbf{Job}_{it}, \mathbf{X}_{it}\right) - \mathbb{E}\left(y_{it} \mid D_t = 0, \mathbf{Kid}_{it}, \mathbf{Job}_{it}, \mathbf{X}_{it}\right)$$

$$= \boldsymbol{\theta}_2\,\mathbf{Kid}_{it} + \boldsymbol{\theta}_3\,\mathrm{F}_i \times \mathbf{Kid}_{it} + \boldsymbol{\theta}_5\,\mathbf{Job}_{it} \quad (8)$$

The pandemic-induced change in the aggregate gender gap is therefore,

$$\triangle G \equiv \mathbb{E}\left[\frac{\partial y_{it}}{\partial D_t} \mid F_i = 1\right] - \mathbb{E}\left[\frac{\partial y_{it}}{\partial D_t} \mid F_i = 0\right] \quad (9)$$

Plugging in (8) and evaluating the expectations,

$$\triangle G = \sum_k (\theta_{2,k} + \theta_{3,k})\,\mathrm{P}\left[\mathrm{Kid}_{it} = k \mid \mathrm{F}_i = 1\right] + \sum_j \theta_{5,j}\,\mathrm{P}\left[\mathrm{Job}_{it} = j \mid \mathrm{F}_i = 1\right] - \sum_k \theta_{2,k}\mathrm{P}\left[\mathrm{Kid}_{it} = k \mid \mathrm{F}_i = 0\right] - \sum_j \theta_{5,j}\,\mathrm{P}\left[\mathrm{Job}_{it} = j \mid \mathrm{F}_i = 0\right] \quad (10)$$

Combining occupation effects, and adding and subtracting the cross-products between the no child group, $\theta_{\cdot,none}$, and the population weights for those with young or school age kids yields,

$$\triangle G = \sum_{k \in \{\text{pre-K,school}\}} (\theta_{2,k} - \theta_{2,\text{none}})\left(\mathrm{P}\left[\mathrm{Kid}_{it} = k \mid \mathrm{F}_i = 1\right] - \mathrm{P}\left[\mathrm{Kid}_{it} = k \mid \mathrm{F}_i = 0\right]\right) \quad (11)$$

$$+ \sum_{k \in \{\text{pre-K,school}\}} (\theta_{3,k} - \theta_{3,\text{none}})\,\mathrm{P}\left[\mathrm{Kid}_{it} = k \mid \mathrm{F}_i = 1\right] \quad (12)$$

$$+ \sum_{j \in \{\text{occ}\times\text{ind}\}} \theta_{5,j}\,\left(\mathrm{P}\left[\mathrm{Job}_{it} = j \mid \mathrm{F}_i = 1\right] - \mathrm{P}\left[\mathrm{Job}_{it} = j \mid \mathrm{F}_i = 0\right]\right) \quad (13)$$

$$+ \theta_{3,\text{none}} \quad (14)$$

which provides the basis for our decomposition.[46] Lines (11) and (12) represent the childcare channel. The first component in (11) captures the impact on the gender gap from differences in child-parent cohabitation patterns (e.g., single motherhood is more prevalent than single fatherhood). The Pandemic's labor supply effect on all those with kids k is given by $\theta_{2,k}$. Though this is common to everyone (men and women) it still contributes to the aggregate gender gap because amongst single households, children are much more likely to live with their mothers. Note that if all households had a father and mother present, this term's contribution to the aggregate gender gap would be zero. The second component in (12) captures the direct effects of the *micro* gender gaps induced by the pandemic that are associated with the presence of kids.

Line (13) captures changes in the gender gap stemming from pandemic-induced changes in labor demand. The contribution of this channel depends on the pandemic's direct effect on each occupation, $\theta_{5,j}$, and differences in the composition of employment by gender, $P(\text{Job}_{it} \mid \text{F}_i)$. Note that this channel has a large effect on the aggregate gender gap when women are disproportionately employed in sectors hit especially hard by the Pandemic. If there were no differences in occupation choice by gender, the contribution of this channel would be zero. The final term in line (14) is the model's residual. It consists of $\theta_{3,\text{none}}$, which captures changes in the labor supply of women with no kids relative to men with no kids that are not accounted for by the occupation effects $\boldsymbol{\theta}_5$.

Finally, evaluating the decomposition requires defining a reference population for which the composition weights in lines (11) - (13) can be calculated. We implement the decomposition for the employed population in our pre-pandemic sample, by conditioning (9) on sub-population $D_t = 0$.

Robustness: Our preferred decomposition in Table 9 uses coefficients estimated from the whole population, as these comport with the results reported in Tables 7 and 8 in the text. As a robustness check, we re-estimate the coefficients on just the employed population and reconduct the decomposition. As expected, a much larger share is attributed now to the occupational channel and the residual is much lower.

[46] Specifically, we add and subtract $\theta_{2,none} \times \text{P}\left[\text{Kid}_{it} = k \mid \text{F}_i = 0\right]$, $\theta_{3,none} \times \text{P}\left[\text{Kid}_{it} = k \mid \text{F}_i = 0\right]$, and $\theta_{2,none} \times \text{P}\left[\text{Kid}_{it} = k \mid \text{F}_i = 1\right]$, for $k \in \{\text{pre-K, school age}\}$. This allows us to define the childcare contributions as the additional change in labor supply for those with children relative to those with no children.

Table D11: Robustness: Decomposition - coefficients from employed population only

Outcome	Childcare	Labor Demand	Residual
hours	21.0%	50.5%	28.5%

E Regression Specification of the Impact over Time

The regression to estimate the impact on the gender gap over time in the US builds on regression (2) and is given by:

$$y_{it} = \gamma_0 + \gamma_1 \, \mathrm{F}_i + \sum_{\tau \in T} \gamma_{2,\tau} \, \mathrm{D}_{\tau,t} + \sum_{\tau \in T} \gamma_{3,\tau} \, \mathrm{F}_i \times \mathrm{D}_{\tau,t} + \boldsymbol{\gamma}_4 \, \mathbf{Job}_{it} + \sum_{\tau \in T} \boldsymbol{\gamma}_{5,\tau} \, \mathbf{Job}_{it} \times \mathrm{D}_{\tau,t} + f_i + \epsilon_{it}. \quad (15)$$

The results in Figure 8 show the estimated coefficients $\gamma_{3,\tau}$ which yield the change in the gender gap relative to January 2020. The f_i denotes individual fixed effects. Note that $\tau \in T$ captures every month between January 2019 and October 2020 excluding January 2020 (i.e., January 2020 is set as the baseline) and, in addition, $D_{\tau,t}$ is a dummy indicating if y_{it} is observed in month τ, i.e., if $t = \tau$.

To extend the analysis and estimate the impact on the gender gap for both child groups – those with and without kids – over time in the US, we adjust the specification (4) in the following way:

$$y_{it} = \boldsymbol{\theta}_0 \, \mathbf{Kid}_{it} + \boldsymbol{\theta}_1 \, \mathrm{F}_i \times \mathbf{Kid}_{it} + \sum_{\tau \in T} \boldsymbol{\theta}_{2,\tau} \, \mathbf{Kid}_{it} \times \mathrm{D}_{\tau,t} + \sum_{\tau \in T} \boldsymbol{\theta}_{3,\tau} \, \mathrm{F}_i \times \mathbf{Kid}_{it} \times \mathrm{D}_{\tau,t} + \boldsymbol{\theta}_4 \, \mathbf{Job}_{it} + \sum_{\tau \in T} \boldsymbol{\theta}_{5,\tau} \, \mathbf{Job}_{it} \times \mathrm{D}_{\tau,t} + f_i + \epsilon_{it}. \quad (16)$$

Figures 9 and 10 depict the resulting coefficients $\theta_{3,\tau}$ by child group (no kid versus with kid below 18) for employment and hours.