Online Appendix for: "From Mancession to Shecession: Women's Employment in Regular and Pandemic Recessions"

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A Additional Tables and Figures

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

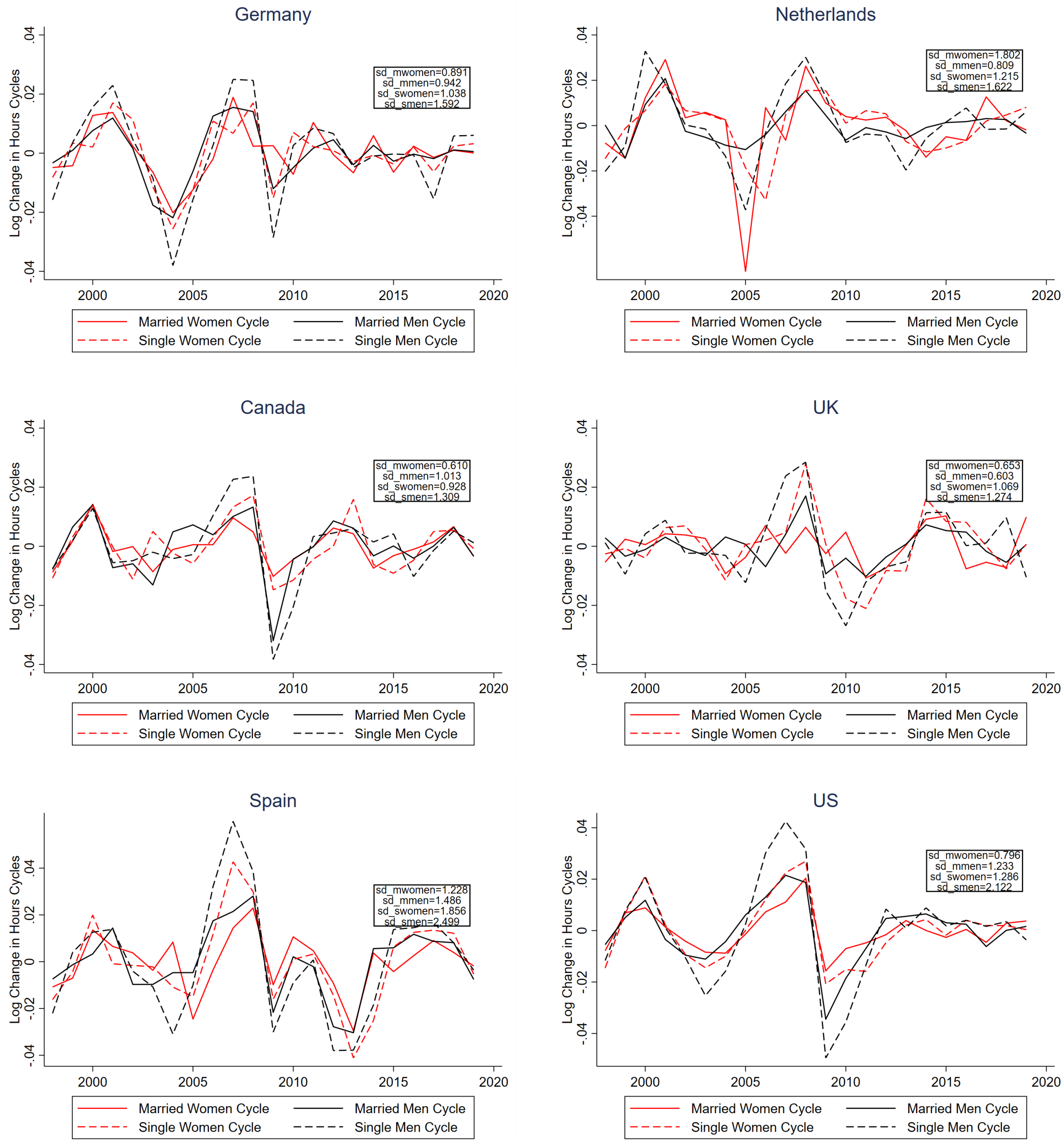
	Percent of all employed individuals (25-54)		
	living with kids	Mothers	Single mothers
Germany	37%	18%	3%
Spain	43%	19%	2%
Netherlands	44%	21%	3%
UK	47%	22%	5%
US	40%	22%	6%
Canada	33%	16%	2%

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

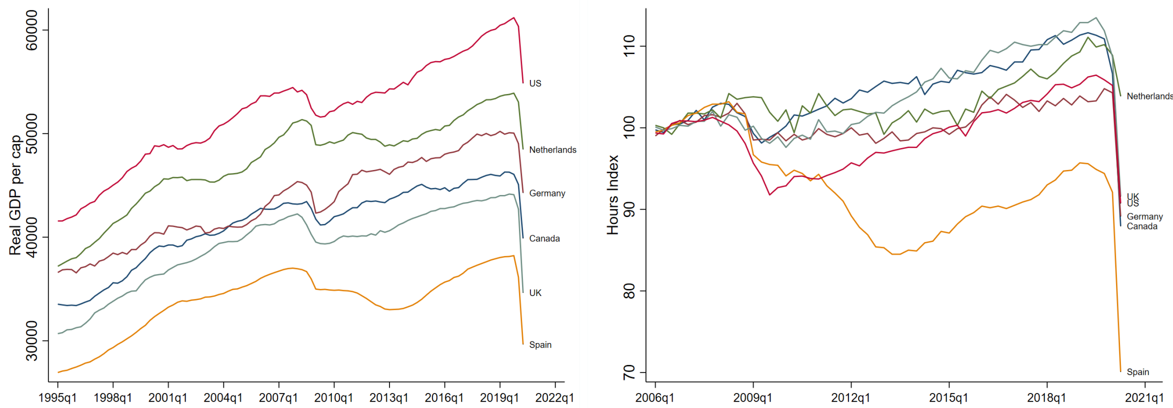
Notes: † *Due to the limitation of data, the child groups are (0-6) and (6-12) for Canada instead of (0-4) and (5-14).*

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



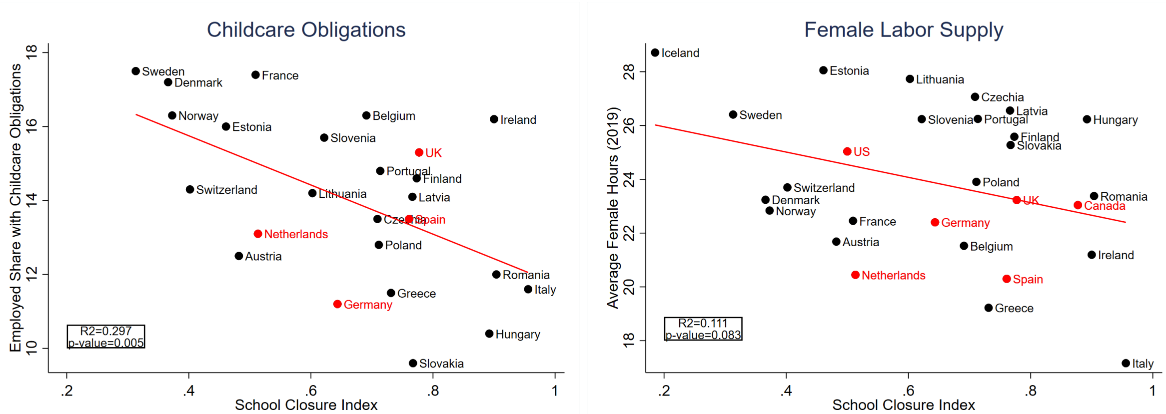
Notes: See Appendix B for data sources.

Figure A2: The Pandemic Recession in Six Countries



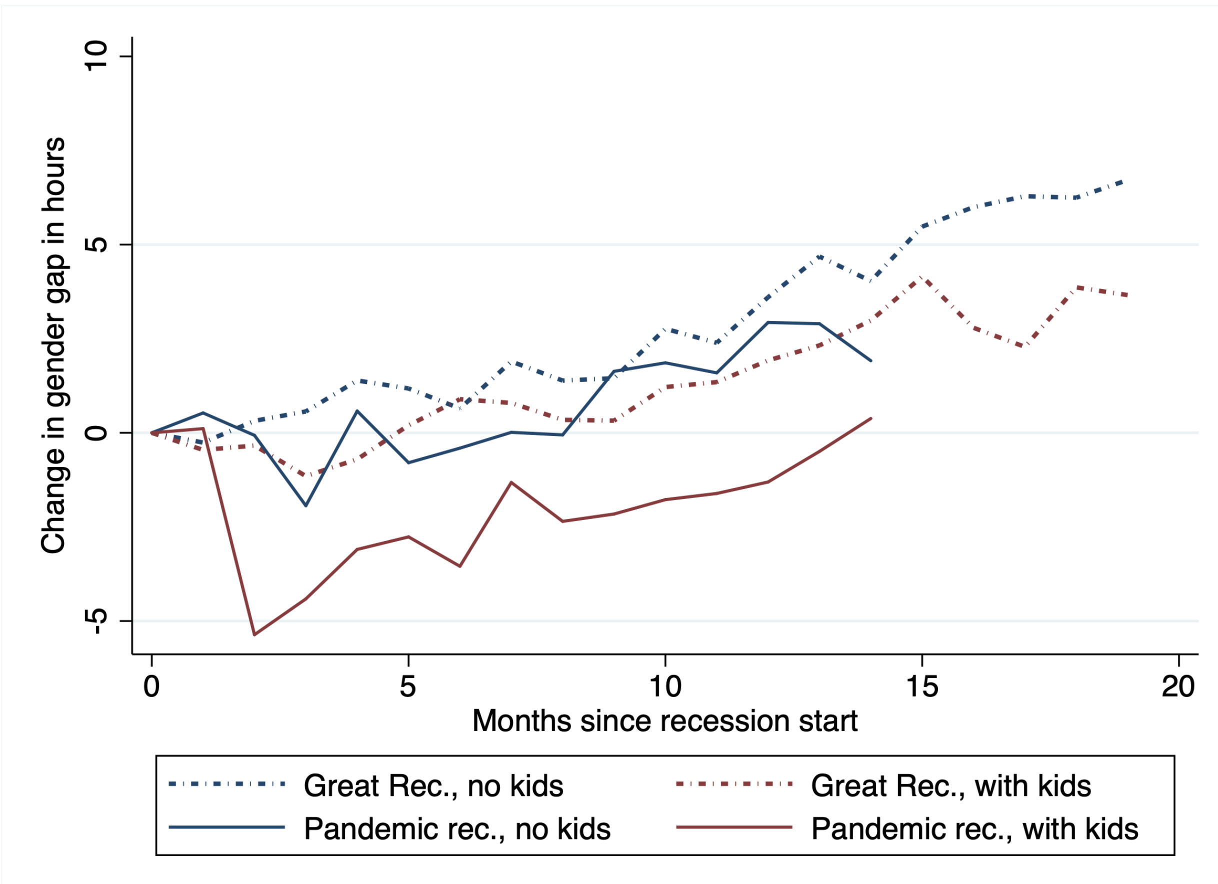
(a) GDP per capita (b) Hours Worked

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. Precovid 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.

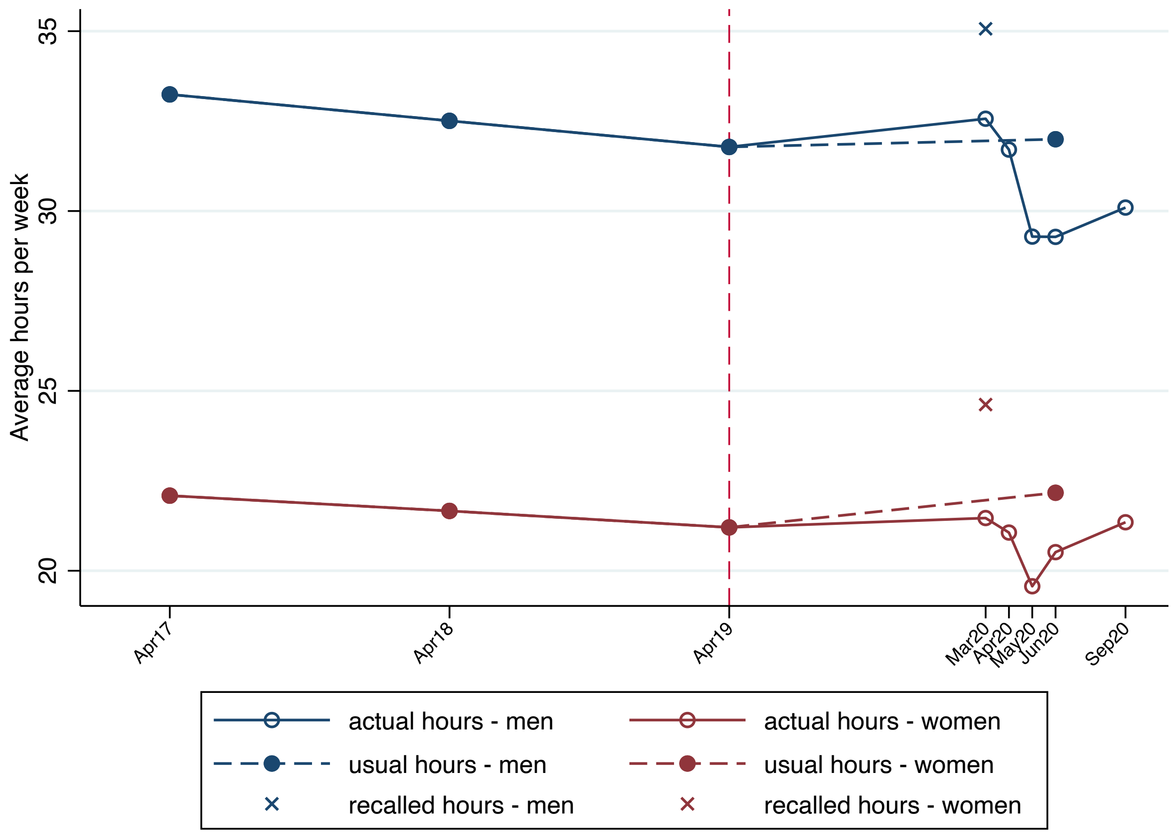
Figure C5 illustrates that the exact phrasing of the question on hours worked is important. In particular comparing questions about hours worked per week with a recall question on the past does not seem to work well as Figure C5 shows quite clearly. A measure of hours worked based on recalling the past 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.