How Has the Increase in Work from Home Impacted the Parental Division of Labor?*

Hans-Martin von Gaudecker[β,ι], Radost Holler[β], Lenard Simon[β], Christian Zimpelmann[ι]

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Abstract

We analyze how parents' flexibility gains through increases in remote work impact their division of non-market and market work. We do so using representative panel survey data and population-wide administrative data from the Netherlands spanning the years 2012–2021. We argue that we are able to isolate the effect of working from home since (1) the remote work potential was realized to a large extent only during the Covid-19 pandemic, (2) schools and daycare were available in the Netherlands throughout the pandemic, with a brief exception in spring 2020, and (3) generous support schemes kept working hours, unemployment and earnings at a similar level as before the pandemic. As a result of the fact that fathers gained more flexibility than mothers, parents divide childcare duties more equally and mothers increase their working hours. These findings suggest that wider acceptance of remote work by employers could lead to greater gender equality in the intra-household division of labor.

Keywords: job flexibility, remote work, childcare, division of labor, time-use data

JEL Classification: J13, J16, J22

*Christian Zimpelmann, IZA – Institute of Labor Economics. Email: zimpelmann[at]iza[dot]org.

†Affiliations: β: Universität Bonn, Department of Economics, Bonn, Germany; Germany; ι: IZA Institute of Labor Economics, Bonn, Germany

1 Introduction

Despite some progress towards gender convergence in the division of labor within households in recent decades, in many countries, mothers still tend to assume a disproportionate share of childcare and domestic responsibilities, while fathers work outside the home. This pattern is at least partially driven by the need for at least one parent's job to be compatible with childcare needs. Most parents must be able to step in at short notice when children are unable to attend school or daycare due to illness or other reasons. These responsibilities are often taken on by mothers, who may choose jobs with fewer hours or greater flexibility in order to accommodate them.

One promising approach to mitigating the gendered division of labor is, thus, to ensure that both parents' jobs are compatible with childcare responsibilities, without altering other factors such as remuneration. A potential avenue to achieve this is by increasing the amount of work that can be done from home, provided that employers do not use this as a means of selecting employees. Working from home inherently involves an increase in time spent at home, as well as a typically higher degree of schedule flexibility and a reduction in commuting time and associated frictions (for the last two items, see Aksoy et al., 2023). Unfortunately, the relation of schedule flexibility and the division of labor within households is difficult to identify as subjects might choose jobs based on their current or expected role in the household.

In this paper, we exploit the way the CoViD-19 pandemic has evolved in the Netherlands to overcome this challenge by examining the strong exogeneous increase in the availability of remote work. We use representative survey data from the LISS Panel, an online survey based on a true probability sample of the Dutch population, combined with administrative labor market records from CBS Netherlands. We argue that among the multitude of effects that the pandemic had on family lives, we can isolate the effects of working from home for several reasons. First, schools and daycare were open in the Netherlands except for two (primary schools and daycare) to three (secondary schools) months in the spring of 2020. Consequently, total hours spent on childcare did not change in the months of November of 2020 or 2021 relative to 2019. Second, generous wage-support schemes were in place, which left income unchanged for most households and helped that the unemployment rate did not move much in general and actually decreased for parents. Third, we show that the potential for working from home has little explanatory power for hours worked from home just before the pandemic. This drastically changed with the onset of the pandemic and the government's advice to work from home. Put differently, the potential to work from home was there before the pandemic, but it was realized to a large extent only after March 2020.

We start out by showing that the gains in job flexibility through the shift to remote work are asymmetrically distributed among parents. On average, fathers gained more flexibility than mothers. This asymmetry is driven by two factors. First, fathers tend to work in jobs with a higher degree of remote work potential. Second, they work more hours, which is more important quantitatively.

Relying on time use data from the LISS Panel, we find that fathers as well as mothers use their newly gained job flexibility for childcare provision. Given the asymmetric changes in job flexibility, the gender gap in childcare provision decreased substantially. Before the pandemic, mothers provided 12.5 more hours of care to their children than their partners. In late 2021, this gap had shrunk to 9 hours. We further show that the potential hours the parents can work remotely strongly predicts childcare hours from 2020 on, but not before. Potential remote hours explain more than half of the decrease in the observed childcare gap.

To investigate the effect of the shift to remote work on labor supply, we use labor market information on the full-population of Dutch parents contained in the Dutch administrative data provided by the Centraal Bureau voor de Statistiek (CBS). The larger and longer panel compared to the time use data of the LISS Panel enables us to detect more subtle changes in the labor supply as well as to implement a more sophisticated identification strategy.

Using the administrative data, we first show that a pre-existing trend of increasing full-time work among mothers accelerated during the pandemic. We then aim to identify whether this acceleration is driven by fathers gaining more job flexibility using an identification strategy that resembles an Event-Study combined with a Difference-in-Differences approach with continuous treatment. That is, we compare the relationship of partners' remote work potential and own working hours over the 2018–2021 period with the same relationship in the years before. We find that mothers and fathers indeed increase their labor supply in response to their partners' newly gained job flexibility. For mothers, we find evidence that roughly half of this effect is driven by reduced commuting time of their partners.

Our results, thus, suggest that increased possibilities to work from home allowed couples to choose a more balanced distribution between market and non-market work. More generally, it highlights that policies which make it easier to combine career ambitions and childcare time can be effective in reducing gender inequality within households.

Our results are related to several strands of the literature. First, women and in particular mothers have preferences for jobs with higher employee-side flexibility and tend to work in more flexible jobs than men. Mas and Pallais (2017) find that in the U.S., mothers of younger children have a higher willingness to pay for remote work, as well as to avoid employer scheduling discretion. Consistent with that, U.S. women have a higher willingness to pay for flexible work arrangements as measured by the option to do part-time work and for job stability (Wiswall and Zafar, 2018). In Germany, Felfe (2012) finds evidence that women who change their job after child birth choose jobs with more schedule flexibility. Magda and Lipowska (2021), studying the distribution of job flexibility all over Europe, find that the likelihood of mothers working in positions with schedule flexibility does not differ strongly from that of fathers, with the exception of Anglo-Saxon countries where mothers are more likely to have schedule flexibility. However, across all countries, women are less likely to work in positions with a high degree of employer scheduling discretion.

Furthermore, even within the same jobs, women choose more flexible working schedules which are more aligned with childcare needs. For example, Houghton (2020) analyzes a wealth of publicly available records of workers' coding activity on GitHub. Examining the impact of unexpected, weather-related public school closures, she finds that women starkly reduce their work activities in response to childcare shocks, while men do not react at all. Similarly, Adams-Prassl (2021) analyzes gender differences in crowdwork on Amazon mechanical turk. She finds that women who do crowdwork are more likely than men who do crowdwork to interrupt their tasks, which leads them to earn 20% lower wages on average. These effects are concentrated among mothers with children at home. Such patterns, however, need not persist everywhere. The overall picture emanating from the literature is that women do take direct wage hits in order to be able to provide childcare. Our paper shows that increased flexibility of the partner can put pressure off mothers to do so.

Second, a set of papers examines the relation of job flexibility and gendered labor market outcomes. Le Barbanchon, Rathelot, and Roulet (2021) find that in France, women search for jobs within a smaller commuting radius than men, which leads to a subsequent wage penalty in outcomes. Meekes and Hassink (2022) find a similar result for the Netherlands among individuals displaced because of firm bankruptcies; women's working hours in their subsequent job are differentially lower than men's, too. Constructing an occupation-level measure of flexibility, Bang (2021) shows that the flexibility of both partners in the year before child birth affects the child penalty. Mothers whose partners are working in flexible jobs experience smaller drops in earnings and wages in the medium run. Pointing to the role of other care options, Cortés and Pan (2019) use inflows of low-wage migrants as an exogenous change in the supply of housework, which leads women to move to occupations with higher returns to long working hours. Goldin (2014) shows that differences in flexibility of work arrangements across genders is strongly related to the remaining gender wage gap.

Our paper complements this literature in two ways. First, these studies typically focus only on the relationship between job flexibility and labor supply while implicitly assuming that the effects operate through childcare provision. We make this explicit, by investigating childcare provision directly. Second and more importantly, we provide the first causal evidence for the effect of job flexibility on labor supply. We take advantage of "windfall" gains in job flexibility induced by the CoVid-19 pandemic and, thereby, circumvent the typically encountered problem that job characteristics and labor supply are jointly determined.

Furthermore, a wide range of studies analyzes the effect of the pandemic on the intra-household allocation of labor. For many countries, there is direct evidence on how couples share the increased childcare burden early in the pandemic while childcare facilities and schools were closed.[1] This evidence is mixed, sometimes even within the same country, but in most cases the childcare gap increased in absolute but decreased in relative terms. Alon et al. (2022) look at the effect on the labor market and find that the pandemic let to a 'shecession' in many countries—however, interestingly not so in the Netherlands. This is consistent with Meekes, Hassink, and Kalb (2020) who find the same (small) negative effects on average for

[1]A non-exhaustive list encompasses data collections in the UK (Andrew et al., 2020; Sevilla and Smith, 2020), Italy (Del Boca et al., 2020; Mangiavacchi, Piccoli, and Pieroni, 2021), Spain (Farré et al., 2020), Germany (Hank and Steinbach, 2020; Jessen et al., 2022), and the US (Pabilonia and Vernon, 2022; Zamarro and Prados, 2021).

men and women and no differential effect for parents in couples. For the US, Heggeness and Suri (2021) find negative labor supply effects for mothers compared to fathers and compared to women without children in a period in which the closure of childcare facilities and schools was frequent in the U.S.. For the first 9 months of the pandemic, they find that negative labor supply shocks were slightly larger for mothers in remote work jobs. Their interpretation is that parents in onsite occupations were not exposed to the same level of intense simultaneous multitasking of increased childcare duties and working. We contribute to this literature in two ways. First, we extend the time horizon to more than one and a half years, thus focusing on the medium term effects of the pandemic. Second, by studying an institutional setting in which childcare facilities and school closures played only a minor role in the medium term, we can isolate the effect of the acceleration in remote work on both labor supply and childcare provision.

Our paper is structured as follows. We describe our data and the basic socio-economic characteristics in the next section. Subsequently, we present the setting of our analysis: The way the pandemic evolved in the Netherlands, background on trends in parents' labor supply and childcare division, and our measures of job flexibility. In Section 4, we present our results on the effects of the pandemic on parents' childcare division and labor supply. We conclude in Section 5.

2 Data

Our study is based on customized survey data from the Longitudinal Internet Studies for the Social Sciences (LISS) panel, population-wide administrative records from Statistics Netherlands, and the Dutch national working conditions survey. Both survey datasets are linked to the population registers at the individual level. We observe household members' time use only in the LISS data, consequently we will use it for all analyses regarding the division of childcare tasks. For analyses of labor supply behavior, we can recur to the population registers, which are several orders of magnitudes larger. However, we do not directly observe the amount of work performed remotely in those data. Hence, we impute a measure for the individual remote work potential based on observed characteristics in the working conditions survey. We describe the datasets in detail in the following subsections.

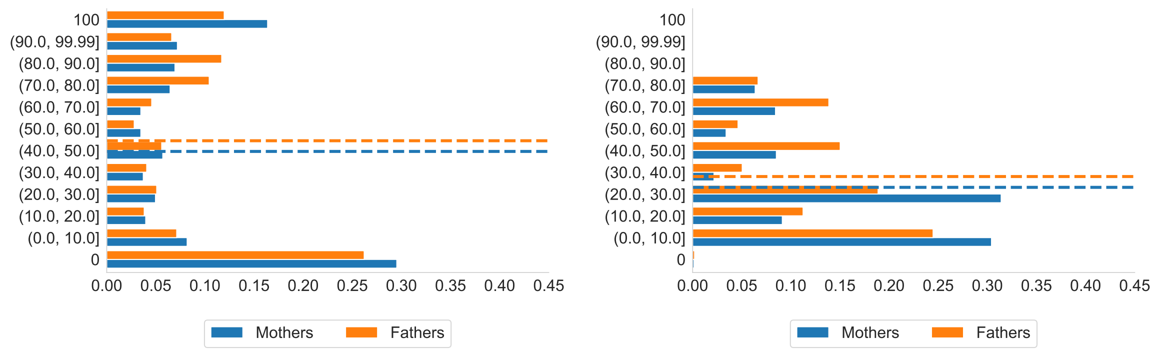
Throughout our analysis, we consider heterosexual couples where both partners are between 18 and 55 years of age and who have at least one child below the age of 16 in the household. The average age of our sample members is a little more than forty years, with a difference of two years between fathers and mothers. The mean number of children is about two; the age of the youngest child is between 6.5 and 7 years.

2.1 Customized survey data from the LISS Panel

The LISS panel is based on a probability sample of individuals registered by Statistics Netherlands; it has been running since 2007 and comprises about 7000 individuals in 4000 households. The LISS panel is administered by CentERdata, a survey research institute affiliated with Tilburg University, the Netherlands. Each year, the LISS panel runs ten core surveys, which cover a wide range of topics, including health, education, work, and family. Taken together, these data are comparable in scope to popular surveys like the Panel Study of Income Dynamics (U.S.), Understanding Society (U.K.), or the Socio-Economic Panel (Germany). On top of that, the LISS panel allows researchers to run their own questionnaires. In this paper, we make use of two sets of surveys that we ran ourselves or helped design.

First, we employ time use information collected in comparable questionnaires in November 2019, April 2020, November 2020, and November 2021. In these surveys, people are asked to distribute the hours of the past week over different activities, including childcare, commuting, work at the usual workplace, and work at home. Appendix A.1 reports more information on the survey; we will describe the evolution of our variables of interest below in Section 3.3.

Second, we make use of a series of CoViD-19 questionnaires (documented in von Gaudecker, Zimpelmann, et al., 2021, see Appendix A.2 for a detailed description) fielded in March–December 2020. Most importantly for this study, we elicit a measure of remote work potential. In May 2020, we ask participants "What percentage of your normal work *prior to the coronavirus outbreak* can you do while working from home?". We interpret the resulting answers to measure remote work potential. That is, the question abstracts from potential changes in jobs or task content due to the pandemic. However, answers should not be affected by employers' demands to come to the workplace. Technological possibilities like videoconferencing had seen widespread adoption, but were already there in February 2020.



(a) Share of tasks that can be done from home (b) Imputed remote work capability (CBS)

Figure 1: Remote working potential by gender

Notes: Figure 1a displays the distribution of the variable "share of tasks that can be done from home" by gender in the LISS sample (403 mothers and 393 fathers). Dashed lines display the mean by gender (45 % for mothers and 49 % for fathers). Figure 1b shows the distribution of the imputed remote work capability by gender in the CBS in the year 2019. For the imputation, we calculate the average remote work capability for all sector $\times$ education combinations in the NEA and impute the remote work capability in the CBS. Dashed lines indicate the mean for each gender (28 % for mothers and 33 % for fathers).

We plot the distribution of measured remote work potential in Figure 1a.[2] The distribution is very polarized. For both genders, more than a quarter of jobs require presence at the workplace for all tasks. At the same time, tasks can entirely be performed remotely in more than 10% of jobs. Average remote work potential is somewhat lower for mothers than for fathers (45 % vs. 49 %). The distribution is in line with other data. For example, a similar question asked in broad samples of the U.S. and U.K. populations returned means of 41–43 % (Adams-Prassl et al., 2022).

Our LISS sample consists of 403 mothers and 393 fathers for whom we have 1,190 and 1,044 observations, respectively, spread over the four waves of the time use survey. Unit non-response leads to some sampling variation across waves.[3] In order to make the descriptive statistics in Section 3.3 more meaningful, we re-weight the sample in terms of age of the youngest child. Doing so has no impact on our main, regression-based results.

[2]In order to reduce measurement error and to increase the sample size, we use the mean of the measure from May 2020 and a similar question asked in December that year; see Appendix A.2.

[3]These numbers already account for individual linkage to the CBS data, which we will describe in the next section. We do so in order to update information on working hours and household composition, which is particularly useful when these individuals did not participate in one or more waves of the survey.

2.2 Population-wide administrative data, Working Conditions Survey

We use detailed administrative microdata on the entire Dutch population from Statistics Netherlands (CBS) for our analyses of labor supply; i.e., anything that does not require time use information. We make use of gender, household composition, education, labor force status (dependent work in full time or part time, self-employment, unemployment, and being outside the labor force), sector, commuting distance, and working hours. We do not observe working hours for the self-employed. The labor market information is recorded monthly for each individual; we extract it for the months of November in the 2012–2021 period. We do so for computational feasibility and to harmonize the timing with the LISS data. We use actual working hours from the first spell in each month. We will describe the trends in these variables in Section 3.2 just below.

The administrative data does not contain direct information on remote work. We thus impute remote work ability based on the National Working Condition Survey (NEA). Using survey information on *actual* remote work in the fall of 2020 from 35,000 individuals, we calculate the average share of remote work. The resulting distribution (see Appendix Figure A.1) has a similar shape as in the LISS data, which is based on a completely different question.[4] We then calculate average remote work potential for all sector × education cells and use the resulting measure in the CBS data, treating it as a time-invariant characteristic. Again, the inherent assumption is that during our period of study, the potential to work remotely was exploited to much larger extent only during the pandemic. See Appendix A.5 for a more detailed description of the imputation procedure and empirical evidence on the (non-) prevalence of remote work before 2020. Figure 1b shows the results for our population-wide data and reveals similar gender differences to the LISS data in Panel a. Because the imputation procedure integrates all within-cell heterogeneity, it comes as no surprise that mass is shifted from the extremes towards the middle of the unit interval.

Dingel and Neiman (2020) use an alternative approach to measure remote work potential. They classify occupations into those that can or cannot be performed from home based on typical tasks and work experiences elicited in surveys. Aggregating over higher level occu-

[4] While differences across genders and the overall shape of the distribution are similar, the means in the NEA data are lower at (28 % for mothers and 33 % for fathers). We attribute this to the fact that even during the pandemic, remote work potential was not fully realized.

pations or industries reveals the share of jobs that can be performed from home. We prefer our directly elicited measure for several reasons. First, tasks within occupations might change at the start of the pandemic in ways which cannot be captured by the descriptions of tasks elicited before the pandemic. Second, our measure is more fine-grained in the sense that it allows respondents to indicate that they can do a part but not all of their work remotely – and more than half of them do so. Finally, it captures differences in remote work potential within occupations (e.g. due to a different firm culture). Adams-Prassl et al. (2022) show their self-reported measure of remote work ability to be strongly related to occupations and sectors, but also find substantial heterogeneity within occupations. While we see this additional hetereogeneity primarily as an advantage, it might raise the concern of response bias on the individual level. Our measure based on the NEA addressed this concern as it is constant within sector $\times$ education cells – while sharing the other two advantages described above (it is based on post-pandemic data and fine-grained). For the analyses based on the LISS sample, we use the self-reported measure of remote work potential. In robustness exercises based on the NEA measure, we obtain very similar results.[5]

3 Setting

In this section, we describe the broader environment for our analysis along with stylized features emanating from our data. First, we illustrate the policy environment during the first two years of the CoViD-19 pandemic. We then highlight some key features of the parental division of labor regarding market and non-market work before and during the pandemic. Finally, we go through our measures of remote work—both the potential for doing so and its realizations—over the period of our analysis.

The contents of this section it becomes clear why we deem it plausible that we can isolate the effect of remote work ability on parents' outcomes during the time period of our analysis.

[5]Hansen et al. (2023) use yet another approach based on job postings to measure realized remote work across industries and sectors over time.

3.1 The CoViD-19 pandemic in the Netherlands

From March 2020 until the end of the our data collection in November 2021, a set of measures were in place to slow the spread of the SARS-CoV-2 virus in the Netherlands. We will describe key features of the policy environment that are relevant for our analysis (Zimpelmann et al., 2021, features a detailed description with a focus on labor market issues). In general, measures were more lenient than in many other countries. In particular, no general curfew or stay-at-home mandate was in place at any point in time.

Figure 2 shows the timeline of relevant government policy measures at the points in time of our data collection in the LISS panel. In November 2019, the world lived in blissful ignorance of SARS-CoV-2's existence. In mid-March 2020, limits on social gatherings were imposed and many businesses involving personal contacts were closed, such as restaurants, bars, and hairdressers. Others like stores for clothes or utilities remained open if they were able to maintain the social distancing rules. Public locations were accessible and the use of public transportation was possible.

Figure 2: Timeline of relevant government policy measures at the points in time of our data collection.

Notes: The policy measures are obtained from the official government recommendations, which can be found on `https://www.government.nl/latest/news`. The unemployment rates are taken from the official statistics from CBS Netherlands.

Many of these restrictions were lifted over the summer of 2020. The majority, however, were in place again during November 2020. After the winter, they were eased again and much milder measures came back in the subsequent fall/winter.

With the onset of the initial restrictions, schools and childcare facilities were closed for a period of two (daycare, primary schools) to three (secondary schools) months. From late spring and summer of 2020 on, policy makers made it very clear that schools and childcare efacilities would be the last institutions to close in case of renewed tightening of restrictions. Except for slightly prolonged vacations around Christmas 2020, this promise was kept. Actual closures were thus very limited in comparison to many other countries.

A comprehensive set of economic support measures accompanied the social distancing restrictions. The largest and most influential policy was the short-term allowance (Noodmaatregel Overbrugging voor Werkgelegenheid, NOW), which subsidized labor hoarding with a 100% wage replacements rate. Dependent employees did not see their incomes drop and there was little movement in unemployment or labor force participation (Zimpelmann et al., 2021). Figure 2 confirms that the overall unemployment rate was low throughout the 2019–2021 period. Starting in March 2020, the government strongly encouraged remote work.

3.2 Market work

Parents' labor force participation was high before the pandemic and increased further during 2020 and 2021. The distribution over different categories of employment (full-time employed, part-time employed, self-employed) or lack thereof (unemployment, out of the labor force) varies considerably with gender. Most notably, mothers' part-time share is very high (about 57% of the population) and at 20% or more in earlier parts of the sample, their share out of the labour force is about twice as high as that of fathers.

Table 1 contains the labor market status for our sample of parents for the months of November in the 2012–2021 period. The first two columns in the upper panel show that the share of mothers who are not working decreased considerably over those years. To be precise, the fraction outside the labor force went from 25% to 19% with the bulk of the decrease happening between 2016 and 2021. The unemployment share decreased from 2.5% to 0.8%.[6] The same trend is present for fathers, albeit at lower levels. The fraction outside the labor force went from 11% to 9.4%; the fraction of unemployed fathers decreased from 2.7% to 0.6%. In 2020, these trends were stalled but continued in 2021.

[6]Note that unemployment is measured as receipt of unemployment benefits, so by ordinary economic definitions, we might be putting some individuals into the wrong category of inactivity.

Table 1: Labor market status over time

	Mothers					Fathers				
	FT	PT	S/E	UE	OOL	FT	PT	S/E	UE	OOL
2012	8.0	58.7	6.1	2.5	24.7	65.4	9.0	12.3	2.7	10.8
2013	7.9	57.5	7.7	2.5	24.6	63.2	9.8	13.5	2.4	11.2
2014	7.8	57.3	8.2	2.1	24.8	61.1	11.8	14.0	1.7	11.5
2015	8.7	56.4	8.7	1.9	24.5	63.4	9.5	14.5	1.4	11.4
2016	9.2	56.2	9.3	1.8	23.7	63.3	9.5	15.1	1.3	10.9
2017	9.2	57.1	9.7	1.4	22.8	62.9	10.1	15.4	1.0	10.7
2018	9.6	57.6	10.2	1.1	21.6	62.7	10.3	16.0	0.8	10.3
2019	10.0	57.8	10.8	1.0	20.5	62.0	10.8	16.7	0.8	9.9
2020	10.5	56.9	11.2	1.1	20.4	61.1	10.8	17.2	0.9	10.0
2021	11.7	56.8	11.7	0.8	19.0	61.3	11.2	17.6	0.6	9.4

Notes: The table shows the labor market status of all working-age (18-55 years old) parents with a child below 16 years of age by year and gender. FT – full-time employed; PT – part-time employed; S/E – self-employed; UE – unemployed; OOL – out of the labor force. Individuals are classified as unemployed when they are receiving unemployment benefits. They are classified as out of the labor force when there are no working hours, no self-employment status, and no unemployment benefits recorded in the administrative data. Consistent with the official definition of CBS Netherlands, we classify individuals to be working part-time if they work less than 35 hours per week. Standard errors are not shown because all of them are below 0.0005 and thus rounded to zero. The data are measured in November of each year and based on administrative data of Statistics Netherlands (CBS).

Figure 2 showed a small increase in overall unemployment and the same is true for inactivity. Hence, parents seem to be even less affected, which may partly be explained by the type of jobs (e.g., very few parents work in the catering sector). Importantly for our purposes, there is no evidence that parents dropped out of the labor force to take care of their children. This stands in stark contrast to countries where schools and daycare facilities were closed for prolonged periods of time (e.g. Heggeness and Suri, 2021)

Mothers' part time employment decreased from up from 59% in 2012 to 57% in 2021. In 2016, 9.2% of mothers were employed full-time – i.e. worked 35 hours or more. The share went up by 0.7 percentage points between 2016 and 2019 and increased by another 1.8 percentage points between 2019 and 2021. Hence, there was a strong acceleration in the increase of mothers' full-time employment during the first two years of the pandemic. As a result, 11.7% of mothers were employed full-time in 2021 as opposed to 9.9% in 2019 and 9.2% in 2016.

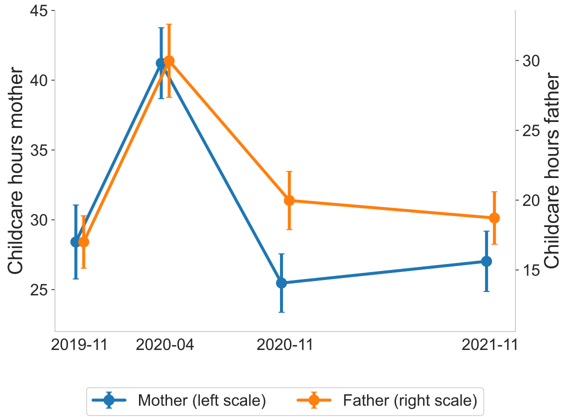
Fathers see a slight decrease in full-time employment and an increase in part-time employment over the observation period. In 2016, 63.1% of fathers worked 35 hours or more, while 9.2% worked less than 35 hours. The share of fathers in full-time employment decreased by 1.4 percentage points between 2016 and 2019, while the share of fathers in part-time employment increased by 1.6 percentage points to 10.8% in 2019. During the pandemic full-time employment dropped by another 0.7 percentage points until November 2020, but recovered again by 0.3 percentage points by November 2021. Hence, decreases in fathers' full-time employment over the entire pandemic period are similar to their pre-pandemic trends. Similarly, part-time employment of fathers increased only by additional 0.3 percentage points over the two years of the pandemic.

The trends described in the previous paragraph hold up when looking at working hours of dependent employees directly instead of categories. In particular, average working hours of mothers increased from 25.2 in 2016 to 26 in 2019. This trend accelerated slightly during the pandemic and by 2021, mothers worked 26.8 hours on average (all numbers referred to in this paragraph are in Appendix Table A.6). Among fathers, average working hours declined slightly from 38.4 in 2016 to 38.1 in 2019 and stayed at this level until the end of our sample period.

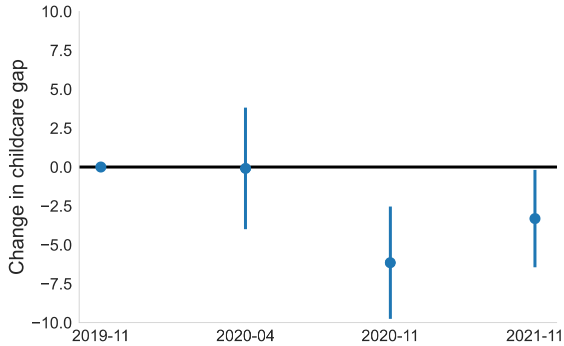
3.3 Non-market work

The flipside of the distribution of market hours is that mothers take on a much larger share of childcare work than men. Figure 3a shows that before the pandemic, mothers on average spent 29 hours per week providing care to their children. Fathers childcare hours, with units depicted on the right axis, were well below that at 17.5 hours. The location of both lines is normalized so they start at the same point, making differences in their evolution salient. During the period of closed schools and daycare facilities, combined childcare hours went up by about 25. This number is plausible given typical times spent at school/daycare and the fact that emergency childcare was available for parents working in essential occupations.[7] The large increase in April 2020 was distributed about equally among both genders. For the

[7]Easier access to formal childcare was the most relevant difference for essential workers in March-May 2020 and there were no relevant differences after that time; hence we do not mention them elsewhere. See Zimpelmann et al. (2021) for a more detailed analysis of essential worker status.



(a) Childcare hours



(b) Change in the childcare gap

Figure 3: Evolution of the childcare gap 2019–2021.

Notes: Figure 3a shows the development of childcare hours by mothers and fathers in the LISS time use data. Figure 3b shows the development of differences in childcare provision between fathers and mothers. The latter is based on a regression of childcare hours on the interaction of time dummies and gender, including as additional controls the number of children, and the standardized age of the youngest child interacted with gender. Standard errors clustered on the household level. The regression coefficients underlying the Figure are listed in Column (1) of Table 3.

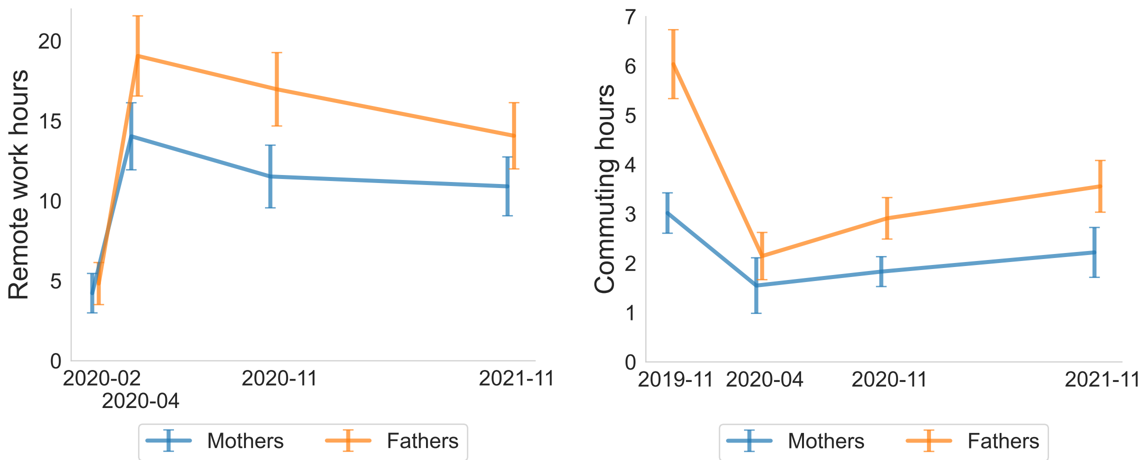
surveys conducted in November 2020 and November 2021, mothers' childcare hours were back to their pre-pandemic levels; in 2020 they might have been a little lower even. Fathers' hours also declined again, but at a lower rate. As a result they spent about two more hours on childcare duties than before the pandemic.

A different way to look at it is to consider the gap between genders directly. Figure 3b visualizes the result of this exercise, showing that the gender differences we described in the previous paragraphs are very robust in statistical terms. There virtually was no change in the gender gap in April 2020. Subsequently, the difference shrank by 3–6 hours. When accounting for statistical uncertainty, a range from 1 to 9 hours seems possible.

We will argue below that the change in the gender care gap can be largely explained by increased flexibility of parents when it comes to their work schedule and location. Next, we thus describe how remote work and commuting evolved over our period of study.

3.4 Remote work and commuting

As early as 2016, the Netherlands introduced a law aimed at facilitating flexible work (Wet flexibel werken). This law defines processes and rights for employees to request adjustments to their working hours, their work schedules, or their work location. Before the CoViD-19 crisis, however, the effects were limited. E.g., ten Hoeve et al. (2021) find that 16% of employees made a request regarding flexible work along *any* of the three dimensions between 2016 and mid-March 2020. Consistent with those findings, our data shows that while 34% of individuals reported to have performed *some* work from home (Appendix Table A.9), mean hours worked from home were below five for both genders (Figure 4a). To put this into perspective, this is an hour less than fathers spent on their weekly commutes on average (Figure 4b). Mothers' mean commuting time was half of that amount at three hours.



(a) Remote working hours

(b) Commuting hours

Figure 4: Realized work from home and commuting over time

Notes: Panel a displays average remote working hours in the LISS sample over time and by gender. Figure 4b displays average commuting hours in the LISS sample over time and by gender. For underlying numbers see Tables A.7 and A.8. Additionally, Table A.9 contains the evolution over time and by gender of a variable measuring *any* remote work and Table A.10 contains the evolution over time and by gender of the share of remote work. In the pre-pandemic period, remote working hours are measured in February 2020 and commuting hours in November 2019.

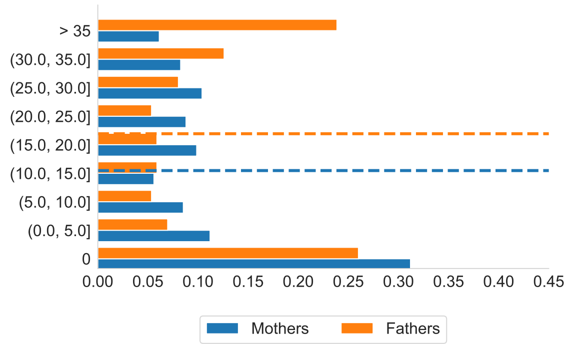
With the onset of the pandemic, these numbers changed dramatically for all parents. In April 2020, weekly hours worked from home increased to 14 among mothers and 19 among fathers. Put differently, about fifty percent of actual hours were done from home. Commuting time dropped to 1.5 hours for mothers and 2.1 hours for fathers. Even as the pandemic progressed, all these numbers remained closer to the values they took during the initial lockdown than to their prior levels.

Actual remote work in the LISS data is consistent with the corresponding numbers from the much-larger working conditions survey (NEA, see Section 2.2). The NEA data also reveal a stark increase in remote work of parents during the pandemic, from approximately 2.8 hours in late 2019 to 10 hours in late 2020. Further, investigating the remote work share by sectors (as a proxy for remote work potential), we find that in the pre-pandemic period, sectors only mildly predict the remote work share of their workers, while in late 2020 the share of hours a worker works remotely strongly depends on the sector he or she works in.[8] This supports our previous point that during the pandemic, remote work potential becomes much more important for its take-up, while take-up is more idiosyncratic before the pandemic.

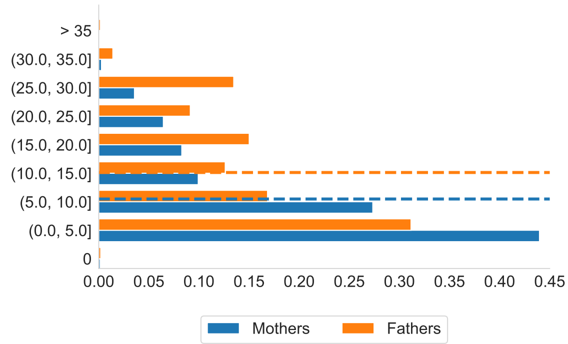
The large increase in remote work implies a large flexibility gain for parents in the period after the summer of 2020, i.e., when schools and daycare were functioning normally again. In order to quantify the potential flexibility gains when it comes to providing for children, we compute potential remote working hours. We do so by multiplying the remote work share as described in Section 2 with working hours just before the pandemic. Figure 5 shows the distribution this measure of potential remote working hours. Compared to Figure 1, the differences between genders are substantially larger in relative terms because men work longer hours. In the LISS data, shown in Panel a, more than 30 % of fathers can work at least 30 hours from home, while only 15 % of mothers can do so. The averages are 19.4 and 13 weekly hours, respectively. In the CBS data, we can see a similar pattern but with a less polarized distribution. Mothers have, on average, a remote work capability of around 8 hours, while fathers have an average of around 12.6 hours.

Table 2 shows that before the pandemic, each potential hour of remote work translated into 12 minutes of actual remote work (this is implied by the coefficient of 0.21 in the second column). In 2020, the coefficient increases to more than 0.8, implying that individuals worked more than 45 minutes remotely for every hour they could potentially do so. In late 2021, when overall remote work was slightly lower and more individuals may have changed jobs, the coefficient drops somewhat but remains high at 0.6 (i.e., 35 minutes for every potential hour).

[8] Details are in Appendix Section A.5.



(a) Potential remote working hours



(b) Potential hours of remote work (CBS)

Figure 5: Remote working potential by gender

Notes: Panel a shows the distribution of the variable potential remote work hours by gender in the LISS sample. Potential remote working hours are calculated by multiplying the share of tasks that can be done from home with the pre-covid (November 2019) working hours of an individual. Dashed lines display the gender-specific means (13 hours for mothers and 19.4 hours for fathers). Samples conditional on working before the pandemic.
Panel b shows the distribution of the potential hours of remote work by gender in the CBS in the year 2019. Dashed lines indicate the mean for each gender (8 hours for mothers and 12.6 hours for fathers). For the imputation we calculate the average remote work capability by sector and education in the NEA and impute the remote work capability in the CBS with the help of those two variables. The imputed remote work capability is then multiplied with the working hours two years ago to obtain the potential hours of remote work.

Table 2: Predictive power of potential remote working hours for realized hours worked from home and commuting time

	Remote working hours		Commuting hours	
	(1)	(2)	(3)	(4)
Constant	5.68***	1.49*	4.63***	4.06***
	(1.25)	(0.79)	(0.28)	(0.38)
2020-04	12.0***	2.61***	−2.7***	−0.95*
	(0.92)	(0.86)	(0.29)	(0.50)
2020-11	9.74***	−0.16	−2.19***	−0.78**
	(0.86)	(0.68)	(0.22)	(0.34)
2021-11	7.92***	0.87	−1.65***	−0.16
	(0.82)	(0.91)	(0.27)	(0.48)
Pot. hours remote work		0.21***		0.04**
		(0.04)		(0.02)
Pot. hours remote work × 2020-04		0.63***		−0.11***
		(0.06)		(0.02)
Pot. hours remote work × 2020-11		0.61***		−0.09***
		(0.05)		(0.02)
Pot. hours remote work × 2021-11		0.42***		−0.09***
		(0.05)		(0.02)
Observations	1,876	1,876	1,876	1,876
R^2	0.081	0.471	0.069	0.11

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level. Sample conditional on working pre-CoVid. Baseline commuting hours based on LISS Time Use Survey from November 2019. Baseline remote work hours obtained from LISS Covid-19 Survey and based on February 2020. Sample restricted on parents who work in November 2019. For the full table see Table B.1 in the Appendix. For the the interaction by gender see Table B.2 in the appendix.

Column (4) of Table 2 reveals an even stronger pattern for realized commuting time as the dependent variable. Prior to the pandemic, a 40 hour job with the potential to do all tasks at home was associated 1.6 hours *more* time spent commuting compared to a job that would not admit any remote work. After the pandemic's onset, the relationship was reversed and commuting time was about 4 hours *less* for a person who works full-time and can do all his tasks from home.

Summing up, we find that remote working hours have strongly increased during the pandemic years. Before the pandemic, take up of remote work was low and rather idiosyncratic. Because of the pandemic, it became intimately tied to job characteristics. The potential hours that can be worked remotely strongly vary across genders. These hours are closely related to increases in actual remote work during the pandemic and to decreases in time spent commuting.

4 Results

Our main results establish that the trend towards a more equal division of childcare during the pandemic was driven by the amount of flexibility parents gained as their potential to work remotely was realized. Similarly, we show in Section 4.2 that the same households are driving the acceleration of the trend towards mothers working longer hours.

4.1 Childcare

We first establish that the potential to work remotely was negatively related to hours spent on childcare before the pandemic and that this relationship flipped rather dramatically after its onset. Beginning in early 2020, the potential to work remotely is closely associated with more time spent on childcare. We then show that remote work potential largely explains the decrease in the childcare gap between mothers and fathers, established in Section 3.3.

Table 3 brings together the changes in the childcare gap between mothers and fathers and the shift to remote work. Column (1) repeats the numbers underlying Figure 3b, which plotted the coefficients on the indicator variables for mother by time period during the pandemic.[9]

[9] The sample includes non-working parents whose potential hours of remote work are set to zero. We report results only including parents who worked before the pandemic in Appendix Table B.6, results do not change. We prefer the sample in Table 3 because when we condition on a parent working before the pandemic, we

The absolute difference in childcare provision between parents did not change in April 2020, when childcare facilities and schools were closed, because both parents increased their childcare hours in magnitudes. There is a sharp decline (six hours) in the gender gap in childcare in November 2020, which materializes by means of a decrease in childcare provision by mothers and an increase among fathers. The shrinking of the gap carries over to November 2021 but only at half the size.

Our key specification is column (2), which adds the potential hours of remote work. This yields a difference-in-differences design with a continuous treatment variable. The basic assumption is that in the absence of the pandemic, childcare hours would have evolved independently from remote work ability. While this assumption might be too strong, we would likely err in a direction that attenuates our coefficients of interest. In particular, before the pandemic, potential hours of remote work are negatively related with childcare hours. This is partly driven by the somewhat mechanical fact that total working hours are higher among parents with a large number of potential remote working hours. Additionally, jobs with high remote work potential tend to yield relatively high earnings, so—to the extent that income effects dominate—c.p., fathers are more likely to work longer hours and mothers are more likely to return to work early and work longer hours.

In April 2020, during the first lockdown in which childcare facilities and schools were closed, the relation between potential remote hours and childcare hours turns strongly positive. On net, one hour of potential remote work translates into 22 minutes of childcare. In November 2020, when childcare facilities and schools were open again, the relationship becomes somewhat weaker but stays significantly positive. The net effect is still slightly positive in November 2021. From 2020 on, mothers and fathers who can work more hours from home strongly increase their childcare hours compared to the time before the pandemic.

We standardize the potential hours of remote work so that we can compare the evolution of the gender care gap across specification. The coefficients on the mother by time period interactions measure the gender care gap, evaluated at the sample mean of potential hours of remote work.[10] Including the standardized potential hours of remote work in the regression

disproportionately drop mothers, leaving fathers in single-earner households in the sample. Conceptually, we prefer to avoid this imbalance.

[10]Defined as potential hrs remote work (std) = (potential hrs remote work $-$ μ) with the sample mean $\mu = 12.2$.

Table 3: The effect of potential remote working hours on the evolution of the gender care gap

	Hrs childcare		
	(1)	(2)	(3)
Constant	17.28***	18.05***	17.75***
	(1.41)	(1.43)	(1.44)
2020-04	12.8***	10.49***	10.49***
	(1.53)	(1.46)	(1.46)
2020-11	2.96**	1.20	1.69
	(1.29)	(1.29)	(1.26)
2021-11	1.55	0.31	0.36
	(1.19)	(1.20)	(1.23)
Mother	14.01***	12.44***	12.67***
	(2.13)	(2.13)	(2.14)
Mother × 2020-04	−0.09	3.85**	3.74*
	(1.99)	(1.94)	(1.94)
Mother × 2020-11	−6.15***	−3.29*	−3.36*
	(1.84)	(1.87)	(1.86)
Mother × 2021-11	−3.31**	−1.46	−1.34
	(1.60)	(1.63)	(1.62)
Pot. hours remote work (std)		−0.16***	−0.1**
		(0.05)	(0.05)
Pot. hours remote work (std) × 2020-04		0.52***	0.55***
		(0.07)	(0.09)
Pot. hours remote work (std) × 2020-11		0.36***	0.26***
		(0.07)	(0.08)
Pot. hours remote work (std) × 2021-11		0.23***	0.21***
		(0.06)	(0.07)
Pot. hours remote work (std) × Mother			−0.16
			(0.10)
Pot. hours remote work (std) × Mother × 2020-04			−0.05
			(0.14)
Pot. hours remote work (std) × Mother × 2020-11			0.24*
			(0.13)
Pot. hours remote work (std) × Mother × 2021-11			0.04
			(0.13)
Observations	2,234	2,234	2,234
R^2	0.324	0.347	0.349

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level. The potential hours of remote work are standardized to mean zero and unit standard deviation to facilitate comparison of coefficients across columns. All specifications control for the (demeaned) age of the youngest child interacted with gender, as well as indicator variables indicating number of children, the left-out category is a single child. In column (3), we additionally interact the number of children with gender, so that the model is fully satiated. Potential remote work hours are set to zero if the individual did not work before the pandemic. The full set of coefficients can be found in Appendix Table B.5. Appendix Table B.6 shows results for the same specifications restricting the sample to individuals who were working before the pandemic.

diminishes the changes in the gender care gap in November 2020 and November 2021 by cutting coefficients in half, rendering them statistically indistinguishable from zero or marginally so. This indicates that the changes in the gender care gap can be largely explained by the shift to remote work which made, in particular, fathers more available in many families.

Column (3) additionally includes an interaction between standardized potential hours of remote work and the mother dummy. This does not change the previous results. Further, it shows that mothers tend to be more inclined to use their potential hours of remote work for childcare. The effect is, however, only statistically significant for November 2020.

4.2 Labor Supply

The result that remote work induced a decrease in the childcare gap gives rise to the question whether these changes also translate to effects on labor supply. In particular, mothers whose partners are now taking over a larger share of childcare duties might be willing to increase the time spent on market work. In Section 3.2, we saw that the trend of increasing full-time work of mothers accelerated over the 2020–2021 period. In this section, we analyze whether partners' remote work induces individuals to work more and to which extent this effect operates through a direct effect of increased remote working hours and to which extent through reduced commuting.

The mechanisms at play are more subtle and likely to operate with some time lag. In April 2020, there was an immediate need for childcare and parental involvement had to be adjusted instantly. In contrast, changing one's (paid) hours of work requires at least some preparation and potentially negotiations with the employer as well as within the household. Hence, we would expect changes in working hours to lag behind changes in childcare hours. Because effects are rather small, we cannot expect to find much in the LISS data. Hence, we stick to the CBS data only.

To estimate the effects of remote work on labor supply, we apply a similar Diff-in-Diff empirical strategy like in the previous section. Treatment intensity, i.e., remote work potential, is measured in each year based on the job two years prior to the respective year. This allows us to include subjects who are not working in a given year, as long as they have worked two years before. This sample selection is the same for each year and will, hence, not drive our results.

There are three important differences, however. First, we focus on the partners' flexibility gains for obvious endogeneity concerns when it comes to own remote work potential. This is also the effect that is relevant for the mechanism above: When the partner gains flexibility through additional remote work, he may take over more childcare, freeing up potential for me to work more. All regressions control for own remote work potential, however. Second, we run all regressions separately for mothers and fathers; this is just to display the results side-by-side rather than in a stacked way (the model in the previous section was nearly saturated in terms of gender interactions, too). Third and most importantly, we add an event study design on top of the specification because of the time trends in female labor force behavior seen in Section 3.2. That is, one might be worried that these trends are related to working from home potential, e.g., because well-educated office workers might have more progressive gender norms than workers in blue-collar occupations.

Table 4 shows the results of that specifications for the effects of partners' remote work potential on labor supply during the pandemic period and relative to prior 4-year periods. For the pandemic, t=0 refers to November 2019. The first column shows that there is a clear uptick relative to prior periods for mothers whose partner has a large potential for remote work. The coefficient of 0.01 means that when comparing groups of women whose partners are in the lowest category of work from home potential identified in the CBS data (0 to 5 hours) and in the highest category (30 to 35 hours), three in 10 women work one more hour per week (controling among others for own remote work potential).

Part of this is driven by gains from commuting. As shown in column (2), the effect reduces by about 50% when we additionally control for potential commuting gains, defined as potential remote work share two years prior times the commuting distance two years prior.[11] Potential commuting gain of the partner is positively related to increases in working hours compared to

[11] As we have only access to the commuting distance from the year 2014 onwards, we take the commuting distance in the year prior for observations in 2015 and the commuting distance from the year itself for the observations in the year 2014. Importantly, our results remain unchanged if we restrict ourself to only using the periods from 2016 onwards, for which we can calculate the commuting gain measure using the information from the job two years prior.

Table 4: The effect of potential remote working hours on working hours

	Mothers		Fathers	
	(1)	(2)	(3)	(4)
Part: Pot hrs wfh × t = -1 × Pand	0.00	−0.0	−0.002	−0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Part: Pot hrs wfh × t = 1 × Pand	0.008***	0.005**	0.004**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Part: Pot hrs wfh × t = 2 × Pand	0.01***	0.005**	0.009***	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)
Part: Pot comm gain × t = -1 × Pand		0.00		0.004***
		(0.001)		(0.001)
Part: Pot comm gain × t = 1 × Pand		0.003***		0.00
		(0.001)		(0.001)
Part: Pot comm gain × t = 2 × Pand		0.004**		0.001
		(0.001)		(0.002)
R^2	0.175	0.193	0.015	0.018

Notes: This table reports a subset of coefficients of an event study DID regression. The dependent variable is unconditional working hours, i.e., the variable is zero if the individual does not work. The event study is run on the period from 2014 to 2021 on sets of four years (i.e., 2014 to 2017, 2015 to 2018, 2016 to 2019, and 2019 to 2021). Only for the last set of years, the dummy 'Pand' is set to one. As before, we use data from November in each year. We control for the number of children, age, and age of the partner. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the individual level. Full list of coefficients in Table B.9.

pre-pandemic times. For mothers whose partner has low or no potential commuting gain the effect of potential remote work hours is only half of the effect in column (1).

All effects a broadly similar for fathers, though the magnitude of the coefficients tends to be smaller. Because of the smaller baseline differences in flexibility gains of mothers (see Figure 5b), the differences are far smaller. The effect of potential commuting gain of the partner does not seem to be systematically related to the pandemic (column 4).

Our results are very robust to alternative specifications. In Table B.7, we use the remote work share instead of potential remote work hours as treatment variable. Results are very similar for mothers while we find a marginally significant pre-trend for fathers. Moreover, imputing remote work share based on sector times education times gender instead of only sector times education does not alter any of our main results.

5 Conclusion

We have investigated how the acceleration in the shift towards remote work during the CoViD-19 pandemic has impacted the division of childcare duties and working hours. The way the pandemic has been handled in the Netherlands—the most important feature being relative short school and daycare closures—has allowed us to isolate this effect. Our analysis has relied on self-collected survey data and population-wide administrative data.

We find that the average gap between mothers' and fathers' childcare provision shrinks by 3.4 hours or 27 % in the period from November 2019 to November 2021. Most of this decline can be attributed to households where the remote work potential of the father was high. The partner's potential remote work also helps to explain the trend towards mothers working longer hours, which accelerated during the pandemic.

Our results show that remote work can help many households to find a division of labor that is more equal across genders. It is likely that more working from home will remain very common in the future, so employers will be less able to condition wages and career progression on it than they were before the pandemic. This also means that a convenient excuse for some parents, in particular fathers, for not being available for childcare duties is gone on some days.

In other institutional environments, the effects we found might take longer to materialize. The infrastructure for remote work and childcare is well-developed and reliable in the Netherlands. Mothers had a high labor force participation rate—albeit with low hours—already before the pandemic, while fathers' weekly hours were low in international comparison (Bick, Brüggemann, and Fuchs-Schündeln, 2019). Finally, of course, in many countries the pandemic had a differentially larger direct effect on the labor market outcomes of women (Alon et al., 2022).

Overall, our results have shown that working from home might have a bright side in bringing about more gender equality within households.

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Appendix A Details on datasets and data

A.1 Time-use data LISS

The time-use data is usually collected every other year in the LISS panel, but the design of the questionnaire changed in November 2019. During the pandemic, two additional waves were added. In the study, we employ time use information collected in comparable questionnaires in November 2019, April 2020, November 2020, and November 2021. In these surveys, people are asked to distribute the hours of the past week over different activities. We use the information on time spent working (beginning with the April 2020 wave, these hours are recorded separately by whether work was done at the usual workplace or at home), commuting, and on childcare. See Been and Centerdata (2021), van Soest et al. (2019), and von Gaudecker and Centerdata (2020a,b), respectively, for the documentation of the four questionnaires.

A.2 COVID-19 modules LISS

We fielded six questionnaires on the impact that the CoViD-19 pandemic had on peoples' lives in the period between mid-March and December 2020 (the questionnaires are documented in von Gaudecker, Zimpelmann, et al., 2021). From those surveys, we employ two variables. We will use the working hours at the point in time before the pandemic started affecting working lives. Most importantly, we measure remote work potential. In May 2020, we ask participants "What percentage of your normal work *prior to the coronavirus outbreak* can you do while working from home?". We repeated this question in December 2020, but inquired about the share of tasks at the current job that can be done from home instead of the pre-pandemic situation.[12]

We repeated this question in December 2020, but inquired about the share of tasks at the current job that can be done from home instead of the pre-pandemic situation: "What percentage of your normal work can you do while working from home?". Motivated by a high correlation between the May and December measures (0.82), we take the mean of the data that is available at the individual level.

[12]The question in December 2020 reads: "What percentage of your normal work can you do while working from home?".

The resulting answers measure the remote work potential, abstracting from any changes in task content that happened during the period of social distancing. The fact that we ask this when the pandemic was already in full swing allows individuals to better assess the *potential* for remote work – it would not have occurred to many people that essentially all meetings could be held in virtual formats. Put differently, we assume that the potential to work remotely was utilized to (almost) full extent only when the government strongly advised doing so as a component of social distancing. The correlation between the May and December measures is 0.82.[13] Reassured by the measures' high degree of stability, we take the mean of the data that is available at the individual level (participation is not identical across waves).

A.3 Description of variables

This section provides further information about the source and calculation of variables in the LISS sample (used for all time-use analyses) and in the full population sample.

LISS sample

Age, gender Obtained from the background questionnaire.

Education Obtained from the administrative records. Based on achieved educational level. The Dutch educational levels are categorized as follows:

Lower secondary and below: primary school, vmbo

Upper secondary: mbo, havo, vwo

Tertiary: hbo, wo

Age of the youngest child Obtained from Covid questionnaire. If possible, we take the information on the age of the youngest child from the administrative records.

Remote work share Obtained from Covid questionnaire. Variable creation is described in detail in Section 2.1.

[13]The Appendix of Zimpelmann et al. (2021) discusses the correlation between the answers in May and December as well as the marginal distributions in great detail.

Potential hours remote work Obtained from Covid questionnaire and time use questionnaire. Variable creation is described in detail in Section 3.4. If possible, we take the information on working hours from the administrative records.

Childcare hours Obtained from time use questionnaire.

Full population sample

Age, gender Obtained from the administrative records.

Education Obtained from the administrative records. Based on achieved educational level. The Dutch educational levels are categorized as follows:

Lower secondary and below: primary school, vmbo

Upper secondary: mbo, havo, vwo

Tertiary: hbo, wo

Age of the youngest child Obtained from the administrative records.

Remote work share Obtained from administrative records. Imputed with the help of the NEA working conditions survey. Imputation is described in detail in Section A.5.

Potential hours remote work Obtained from administrative records. Variable creation is described in detail in Section 4.2.

Commuting distance Obtained from administrative records. Measures the distance from the home to the workplace.

Working hours Obtained from administrative records. Variable creation is described in detail in Section 2.2.

A.4 Descriptive statistics

Table A.1 displays the socio-demographic characteristics in the two samples, we mostly rely on in our analysis pooled across time. It reveals that most socio-demographic statistics line up well between the LISS sample and the population data. Mothers are somewhat younger

Table A.1: Socio-demographic variables by data source and gender pooled over time

	LISS		CBS	
	Fathers	Mothers	Fathers	Mothers
Age	42.56	40.27	41.41	39.0
	(6.51)	(6.42)	(6.99)	(6.72)
Age youngest child	6.75	6.85	6.66	6.7
	(4.69)	(4.74)	(4.83)	(4.86)
Number of children	2.08	2.03	1.96	1.94
	(0.78)	(0.8)	(0.8)	(0.78)
Education: High	0.46	0.47	0.39	0.44
	(0.5)	(0.5)	(0.49)	(0.5)
Education: Middle	0.26	0.27	0.29	0.31
	(0.44)	(0.44)	(0.45)	(0.46)
Education: Low	0.04	0.03	0.08	0.07
	(0.21)	(0.18)	(0.27)	(0.25)
Education: Unknown	0.24	0.23	0.24	0.18
	(0.42)	(0.42)	(0.42)	(0.39)
Observations	1,044	1,190	3,304,273	3,322,747

Notes: The first column displays basic demographic characteristics of the LISS sample by gender pooled over all months. The age variable is taken directly from the LISS survey. The values for the variables age of youngest child and number of children are taken from the administrative records for all linked individuals and from the LISS survey for all those who are not linked. The education variable is taken from the administrative records and therefore only available for linked individuals (note that even for linked individuals it is possible that the education is unknown). The second column displays basic demographic characteristics of the of all working-age (18-55 years old) who were employed some time in 2018 and 2019 parents with a child below 16 years old by gender pooled over November 2018 - November 2021. The education variable is unknown if there is no available administrative record on the education for the individual. See Table A.3 for the numbers over time.

than fathers, families comprise slightly more than 2 children on average and the age of the youngest child falls just below the middle of the age interval we require.

The one exception is that respondents in the LISS panel are better educated. In particular, 3% of parents do not have a secondary degree. This compares to 10% in the CBS data and it is a well-known bias in surveys. The composition of our LISS sample changes somewhat over time. In particular, the average age of the youngest child is lower for mothers who respond in 2021 compared to 2019 and April 2020 (6.3 years vs 7.2 years, see Table A.3a). As this could affect the analysis of childcare hours, we re-weight our sample in terms of age of the youngest child. The waves in 2020 and 2021 are re-weighted such that they match the composition of the sample in 2019, which results in a stable composition over time.

A.5 Imputation of remote work potential in the administrative data

For the imputation of the remote work capability in the administrative records, we make use of the National Working Condition Survey (NEA). It is currently available until 2020, i.e. the wave of 2021 is not yet published. Its goal is to gather information on the topics of working conditions, occupational accidents, work content, employment relationships and employment conditions of employees. The NEA is carried out yearly since 2005 by Statistics Netherlands and TNO, in collaboration with the Ministry of Social Affairs and Employment. Its target population are all employees aged 15 to 74 who work in the Netherlands, from whom a sample is surveyed during the period of 1st of October to 31st of December of each year.[14]

Around 50,000 individuals answer the survey each year and around 30,000 to 35,000 of those respondents answered the questions on remote work, which we use for our imputation. In particular, we use the following variables for calculating a remote work share:

- Remote Work Hours (Afl_AantUurTW): "On average, how many hours a week do you work from home for your employer?"
- Remote Work Dummy (Afl_Telewerk): "Teleworker (works at least half a day a week outside the company location with access to the company's IT system)"
- Working Hours (Afl_Uren): "Working hours in hours per week in current job"

We calculate a remote work share for each individual by dividing the remote work hours by total working hours. For individuals for whom we do not observe information on the remote work hours, but for whom we observe the remote work dummy being 0, we impute a remote work share of 0.

Figure A.1 displays the distribution of the remote work share by gender in the NEA in the year 2020. Dashed vertical lines indicate the mean for each gender. The figure shows that the

[14] The documentation of the survey and all questionnaires are available at `https://www.cbs.nl/nl-nl/onze-diensten/methoden/onderzoeksomschrijvingen/korte-onderzoeksbeschrijvingen/nationale-enquete-arbeidsomstandigheden--nea--`.

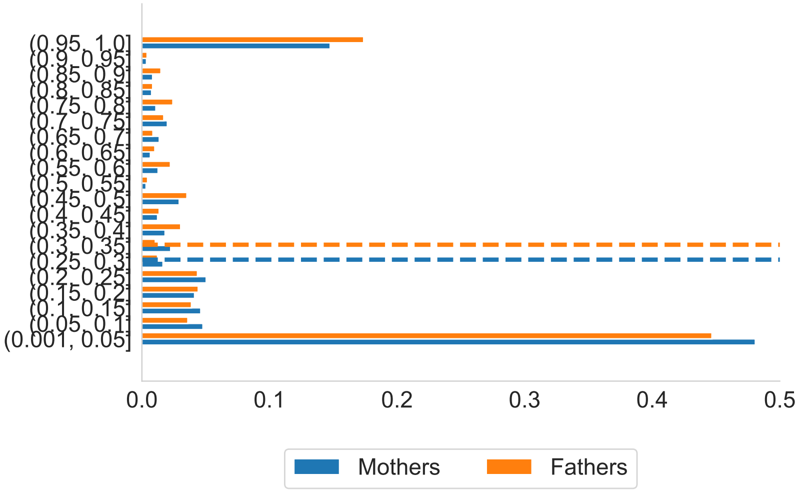


Figure A.1: Remote work capability (NEA)

Notes: Figure A.1 displays the distribution of remote work capability by gender in the National Working Conditions Survey (NEA) in the year 2020. Dashed vertical lines indicate the mean for each gender. Remote work capability is calculated by dividing the hours of remote work by total working hours. The figure shows that the remote work capability in the NEA exhibits a similar distribution like the share of tasks that can be done from home variable in the LISS Sample. The distribution is bi-modal and men work in jobs with an, on average, higher remote work capability than women.

remote work share in the NEA exhibits a similar distribution like the share of tasks that can be done from home variable in the LISS Sample (see Figure 1a). The distribution is bi-modal and men have, on average, a higher remote work share than women.

Figure A.2 displays the mean remote work share aggregated by sector over time. Before the pandemic, remote work shares were on a low level and differences between sectors were much smaller than in the year 2020.

To be able to impute the remote work capability for each individual in the administrative records, we have to find predictive characteristics along which we can make the imputation. Table A.2 displays the regression results from regressing the remote work share in 2020 on education, gender and sector. The table shows that education and sector are highly predictive for the remote work share, while gender is not predictive. We therefore perform the imputation with the help of education and sector.

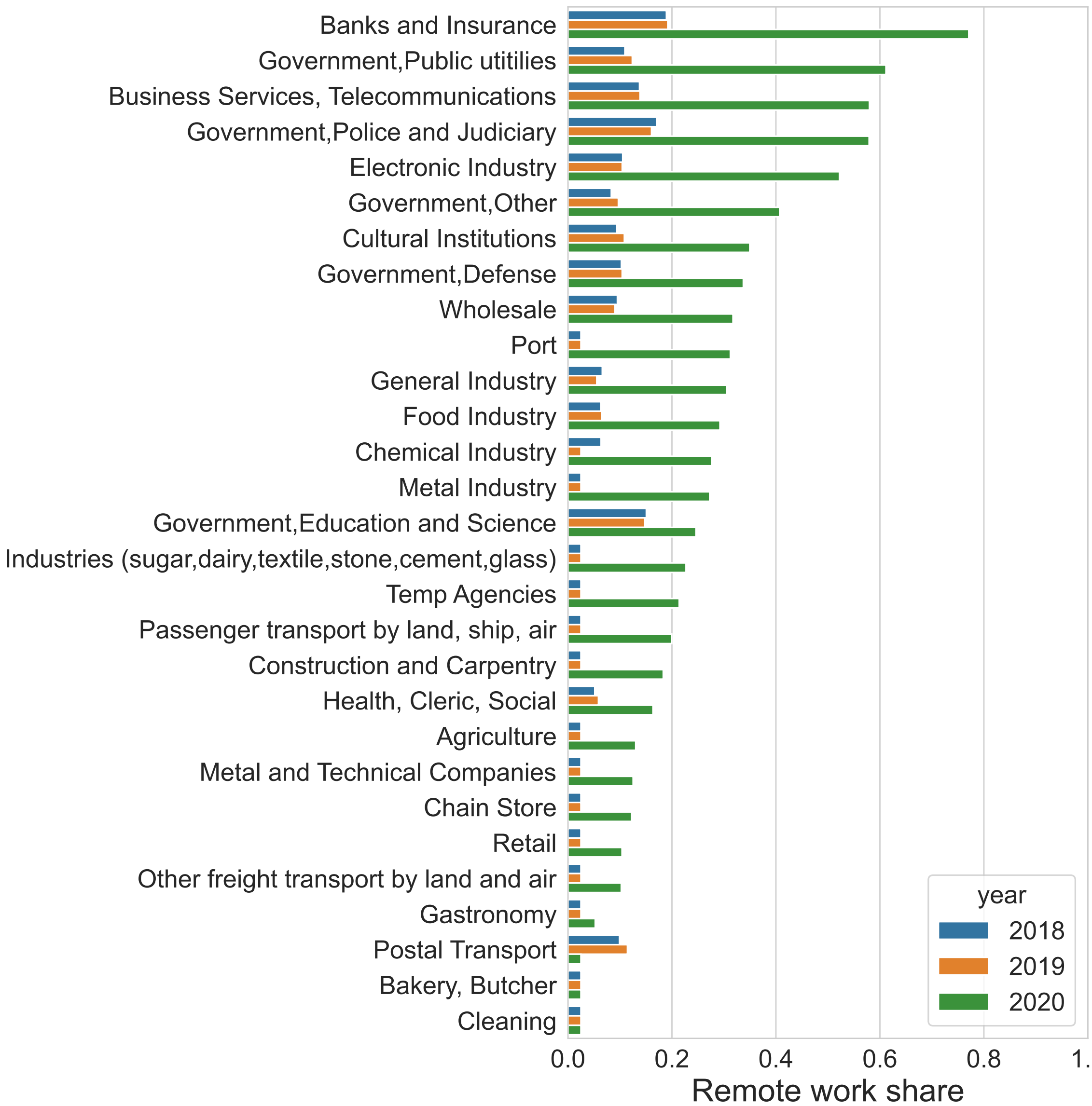


Figure A.2: Share of remote work by sector over time

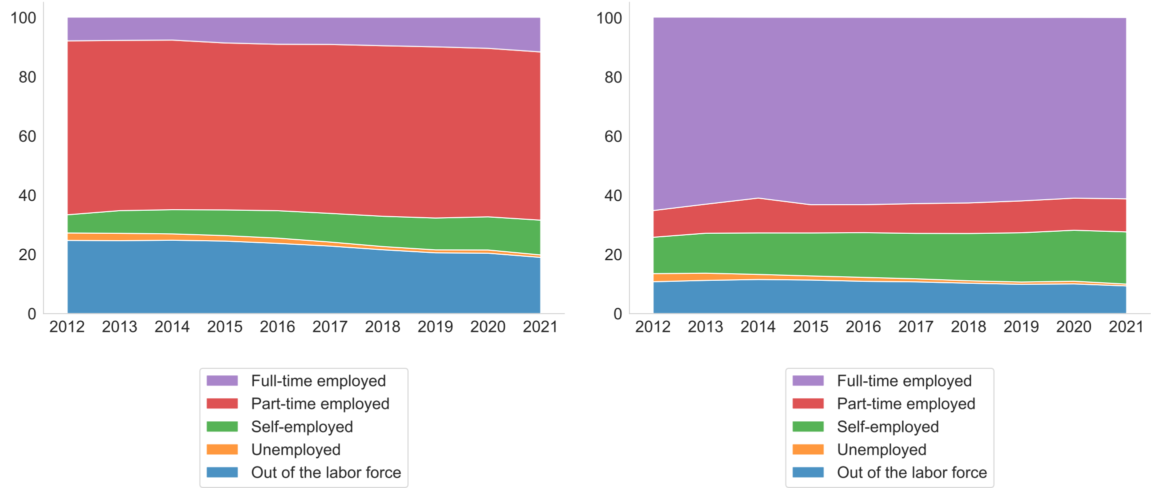
Notes: This figure displays the mean remote work share aggregated by sector for the years 2018, 2019, and 2020. Note that shares below 5 % are anonymised by the export procedure of CBS Netherlands. For this figure, we set those values to 2.5 %. The data is based on the National Working Conditions Survey (NEA) in the respective year.

Table A.2: Determinants remote work share

	2018	2019	2020
Constant	0.18***	0.19***	0.44***
	(0.0048)	(0.0046)	(0.0086)
Education: Low	−0.079***	−0.083***	−0.29***
	(0.0042)	(0.004)	(0.0079)
Education: Middle	−0.067***	−0.062***	−0.19***
	(0.0027)	(0.0024)	(0.0046)
Education: Unknown	−0.045***	−0.042***	−0.16***
	(0.0024)	(0.0022)	(0.0043)
Father	0.018***	0.017***	−0.0044
	(0.0021)	(0.002)	(0.0038)
Agriculture	−0.13***	−0.12***	−0.15***
	(0.0096)	(0.0089)	(0.018)
Bakery, Butcher	−0.13***	−0.14***	−0.21***
	(0.013)	(0.012)	(0.024)
Banks and Insurance	0.014*	0.0085	0.41***
	(0.0078)	(0.0075)	(0.014)
Business Services	−0.035***	−0.041***	0.23***
	(0.005)	(0.0047)	(0.0088)
Chain Store	−0.12***	−0.12***	−0.16***
	(0.0081)	(0.0077)	(0.015)
Chemical Industry	−0.097***	−0.13***	−0.029
	(0.01)	(0.0098)	(0.019)
Cleaning	−0.12***	−0.13***	−0.21***
	(0.0097)	(0.0096)	(0.019)
Construction and Carpentry	−0.12***	−0.13***	−0.1***
	(0.007)	(0.0066)	(0.013)
Cultural Institutions	−0.076***	−0.066***	−0.0071
	(0.013)	(0.013)	(0.023)
Electronic Industry	−0.064***	−0.079***	0.18***
	(0.012)	(0.01)	(0.021)
Food Industry	−0.099***	−0.1***	−0.014
	(0.011)	(0.01)	(0.02)
Gastronomy	−0.12***	−0.12***	−0.22***
	(0.0084)	(0.0077)	(0.016)
General Industry	−0.097***	−0.12***	−0.019
	(0.0084)	(0.0082)	(0.015)
Government, Defense	−0.059***	−0.068***	0.028
	(0.013)	(0.012)	(0.023)
Government, Education	−0.027***	−0.037***	−0.14***
	(0.0049)	(0.0046)	(0.0087)
Government, Other	−0.074***	−0.073***	0.099***
	(0.0075)	(0.0077)	(0.014)
Government, Police	0.0024	−0.016**	0.24***
	(0.0074)	(0.0068)	(0.013)
Government, Public utitilies	−0.058***	−0.053***	0.27***
	(0.0068)	(0.0064)	(0.012)
Health, Cleric, Social	−0.1***	−0.1***	−0.15***
	(0.0049)	(0.0047)	(0.0089)
Industries (sugar, dairy, textile, stone, cement, glass)	−0.12***	−0.12***	−0.076***
	(0.011)	(0.01)	(0.021)
Metal Industry	−0.12***	−0.12***	−0.03**
	(0.0075)	(0.0075)	(0.014)
Metal and technical companies	−0.12***	−0.13***	−0.15***
	(0.006)	(0.0058)	(0.011)
Other freight transport	−0.13***	−0.13***	−0.16***
	(0.0078)	(0.0078)	(0.015)
Passenger transport	−0.12***	−0.13***	−0.093***
	(0.0086)	(0.0083)	(0.016)
Port	−0.1***	−0.12***	0.022
	(0.01)	(0.0092)	(0.021)
Postal Transport	−0.045***	−0.04***	−0.23***
	(0.014)	(0.015)	(0.029)
Retail	−0.12***	−0.12***	−0.17***
	(0.0069)	(0.0065)	(0.013)
Temp Agencies	−0.12***	−0.12***	−0.068***
	(0.0094)	(0.0091)	(0.014)
Wholesale	−0.063***	−0.077***	0.016
	(0.0058)	(0.0055)	(0.01)
N children	0.0036***	0.0031***	−0.0043***
	(0.0009)	(0.0008)	(0.0016)
Observations	31000	38000	37000
R^2	0.12	0.11	0.27

Notes: The table displays the regression results from regressing the remote work share in 2018, 2019 and 2020 on education, gender and sector. The population are all individuals in the NEA sample for whom we have information on actual remote work. The table shows that education and sector are highly predictive for the remote work share, while gender is not predictive. We therefore use education and sector for our imputation.

A.6 Additional descriptive statistics



(a) Mothers (b) Fathers

Figure A.3: Labor force participation and hours categories over time

Notes: The figure provides an illustration of in Table 1. The data source are all working-age (18-55 years old) households with a child below 16 years of age by month and gender. Individuals are classified as unemployed when they are receiving unemployment benefits and classified as out of the labor force when there are no working hours, no self-employment status, and no unemployment benefits recorded in the administrative data. Consistent with the official definition of CBS Netherlands, we classify individuals to be working part-time if they work less than 35 hours per week.

Table A.3: Basic demographics by data source and gender over time

(a) LISS

		Age	Age youngest child	Number of children	Education: High	Education: Middle	Education: Low	Education: Unknown	Observations
Mothers	2019-11	40.55	7.17	2.05	0.45	0.26	0.03	0.26	260
		(0.38)	(0.28)	(0.05)	(0.03)	(0.03)	(0.01)	(0.03)	
	2020-04	40.90	7.18	2.05	0.45	0.25	0.05	0.25	280
		(0.37)	(0.29)	(0.05)	(0.03)	(0.03)	(0.01)	(0.03)	
	2020-11	40.09	6.85	2.03	0.44	0.26	0.04	0.26	339
		(0.35)	(0.26)	(0.04)	(0.03)	(0.02)	(0.01)	(0.02)	
	2021-11	39.68	6.29	2.01	0.54	0.30	0.02	0.14	311
		(0.38)	(0.27)	(0.05)	(0.03)	(0.03)	(0.01)	(0.02)	
Fathers	2019-11	42.63	6.94	2.10	0.48	0.25	0.03	0.24	229
		(0.41)	(0.30)	(0.05)	(0.03)	(0.03)	(0.01)	(0.03)	
	2020-04	42.96	6.80	2.07	0.42	0.27	0.05	0.25	257
		(0.41)	(0.30)	(0.05)	(0.03)	(0.03)	(0.01)	(0.03)	
	2020-11	42.33	6.69	2.07	0.43	0.25	0.05	0.27	283
		(0.39)	(0.28)	(0.05)	(0.03)	(0.03)	(0.01)	(0.03)	
	2021-11	42.35	6.60	2.08	0.51	0.27	0.04	0.18	275
		(0.40)	(0.29)	(0.05)	(0.03)	(0.03)	(0.01)	(0.02)	

(b) CBS

		Education: High	Education: Middle	Education: Low	Education: Unknown	Observations
Mothers	2016-11	0.36	0.28	0.11	0.25	268113
		(0.00)	(0.00)	(0.00)	(0.00)	
	2017-11	0.37	0.29	0.10	0.24	264208
		(0.00)	(0.00)	(0.00)	(0.00)	
	2018-11	0.39	0.29	0.10	0.23	261210
		(0.00)	(0.00)	(0.00)	(0.00)	
	2019-11	0.40	0.29	0.10	0.21	258413
		(0.00)	(0.00)	(0.00)	(0.00)	
	2020-11	0.41	0.30	0.09	0.20	254761
		(0.00)	(0.00)	(0.00)	(0.00)	
	2021-11	0.42	0.30	0.09	0.19	254539
		(0.00)	(0.00)	(0.00)	(0.00)	
Fathers	2016-11	0.34	0.26	0.10	0.30	268113
		(0.00)	(0.00)	(0.00)	(0.00)	
	2017-11	0.35	0.26	0.10	0.29	264208
		(0.00)	(0.00)	(0.00)	(0.00)	
	2018-11	0.36	0.27	0.10	0.27	261210
		(0.00)	(0.00)	(0.00)	(0.00)	
	2019-11	0.36	0.28	0.10	0.26	258413
		(0.00)	(0.00)	(0.00)	(0.00)	
	2020-11	0.37	0.29	0.10	0.24	254761
		(0.00)	(0.00)	(0.00)	(0.00)	
	2021-11	0.38	0.30	0.09	0.23	254539
		(0.00)	(0.00)	(0.00)	(0.00)	

Notes: Table A.3a displays means and standard errors of basic demographic characteristics of the LISS sample by month and gender. The age variable is taken directly from the LISS survey. The values for the variables age of youngest child and number of children are taken from the administrative records for all linked individuals and from the LISS survey for all those who are not linked. The education variable is taken from the administrative records and therefore only available for linked individuals (note that even for linked individuals it is possible that the education is unknown). Table A.3a displays means and standard errors of basic demographic characteristics of all working-age (18-55 years old) parents with a child below 16 years old by month and gender. The education variable is unknown if there is no available administrative record on the education for the individual.

Table A.4: Basic demographics, CBS sample for the analysis in Section 4.2

	Mothers		Fathers	
	Control: 2013-2016	Treated: 2018-2021	Control: 2013-2016	Treated: 2018-2021
Age	39.07	39.0	41.47	41.41
	(6.61)	(6.72)	(6.84)	(6.99)
Age youngest child	6.76	6.7	6.76	6.66
	(4.84)	(4.86)	(4.84)	(4.83)
Education: High	0.38	0.44	0.35	0.39
	(0.48)	(0.5)	(0.48)	(0.49)
Education: Low	0.08	0.07	0.08	0.08
	(0.27)	(0.25)	(0.28)	(0.27)
Education: Middle	0.28	0.31	0.25	0.29
	(0.45)	(0.46)	(0.43)	(0.45)
Education: Unknown	0.27	0.18	0.32	0.24
	(0.44)	(0.39)	(0.46)	(0.42)
Full-time	0.11	0.14	0.83	0.83
	(0.32)	(0.35)	(0.38)	(0.38)
Number of children	1.96	1.94	1.98	1.96
	(0.77)	(0.78)	(0.8)	(0.8)
Out of labor force	0.05	0.04	0.03	0.02
	(0.23)	(0.2)	(0.17)	(0.15)
Part-time	0.83	0.81	0.14	0.14
	(0.38)	(0.4)	(0.34)	(0.35)
Potential commuting gains	6.02	6.11	9.94	10.15
	(12.36)	(11.93)	(16.04)	(16.13)
Potential hours remote work	7.01	7.75	11.77	12.37
	(6.87)	(7.13)	(8.72)	(8.89)
Remote work capability (imputed)	26.65	27.56	31.38	32.35
	(21.73)	(21.52)	(22.93)	(23.02)
Unemployed	0.01	0.01	0.01	0.01
	(0.09)	(0.11)	(0.08)	(0.1)
Working hours	24.55	26.4	38.33	38.59
	(8.37)	(7.99)	(5.78)	(5.6)
Working hours (unconditional)	23.09	25.08	37.01	37.52
	(9.95)	(9.69)	(8.97)	(8.43)
N	3,427,090	3,322,747	3,549,700	3,304,273

Notes: The table displays means and standard deviations of the pooled event-study DiD sample for parents with a youngest child below 16. All variables are reported separately for the treatment and control group and for mothers and fathers. The difference between working hours and unconditional working hours is that the former excludes working hours of 0, while the latter is not conditional on working and therefore includes working hours of 0. Individuals are classified as unemployed when they are receiving unemployment benefits and classified as out of the labor force when there are no working hours, no self-employment status, and no unemployment benefits recorded in the administrative data. Consistent with the official definition of CBS Netherlands, we classify individuals to be working part-time if they work less than 35 hours per week. Imputed remote work capability is calculated with the procedure in Section **??**. Potential hours of remote work are calculated by multiplying the imputed remote work capability with actual working hours for the periods -1 and 0 and then taking the mean of it. Potential commuting gains are calculated by multiplying the imputed remote work capability with the commuting distance for the periods -1 and 0, assuming that all individuals commute on five working days per week, and then taking the mean of it.

Table A.5: Labor market status over time in the LISS data

		Out of the labor force	Unemployed	Self-employed	Part-time employed	Full-time employed
Mothers	2019-11	0.188	0.008	0.131	0.581	0.092
		(0.024)	(0.005)	(0.021)	(0.031)	(0.018)
	2020-04	0.146	0.004	0.140	0.595	0.115
		(0.021)	(0.004)	(0.021)	(0.029)	(0.019)
	2020-11	0.159	0.003	0.109	0.591	0.138
		(0.020)	(0.003)	(0.017)	(0.027)	(0.019)
	2021-11	0.134	0.008	0.122	0.632	0.103
		(0.019)	(0.005)	(0.019)	(0.027)	(0.017)
Fathers	2019-11	0.026	0.000	0.074	0.170	0.729
		(0.011)	(0.000)	(0.017)	(0.025)	(0.029)
	2020-04	0.013	0.004	0.072	0.170	0.740
		(0.007)	(0.004)	(0.016)	(0.023)	(0.027)
	2020-11	0.025	0.003	0.071	0.138	0.763
		(0.009)	(0.003)	(0.015)	(0.020)	(0.025)
	2021-11	0.020	0.003	0.076	0.155	0.746
		(0.008)	(0.004)	(0.016)	(0.022)	(0.026)

Notes: The table shows the labor market participation by month and gender for the LISS sample. For all variables means and standard errors are reported. Individuals are classified as unemployed when they are receiving unemployment benefits and classified as out of the labor force when there are no working hours, no self-employment status, and no unemployment benefits recorded in the administrative data. Consistent with the official definition of CBS Netherlands, we classify individuals to be working part-time if they work less than 35 hours per week.

Table A.6: Total working hours over time

	CBS			LISS		
	All	Fathers	Mothers	All	Fathers	Mothers
2012-11	31.6	38.3	23.9			
	(0.0073)	(0.006)	(0.009)			
2013-11	31.3	37.8	24			
	(0.0072)	(0.0062)	(0.0089)			
2014-11	31	37.2	24.1			
	(0.0071)	(0.0062)	(0.009)			
2015-11	31.7	37.8	24.7			
	(0.0071)	(0.0061)	(0.009)			
2016-11	32.2	38.4	25.2			
	(0.0071)	(0.0062)	(0.009)			
2017-11	32.2	38.2	25.4			
	(0.007)	(0.0062)	(0.0089)			
2018-11	32.3	38.2	25.7			
	(0.0069)	(0.0062)	(0.0087)			
2019-11	32.3	38.1	26	28.5	37.1	20.9
	(0.0068)	(0.0062)	(0.0087)	(0.633)	(0.608)	(0.812)
2020-04				28.6	36.6	21.5
				(0.587)	(0.578)	(0.77)
2020-11	32.4	38	26.3	29.3	37	22.5
	(0.0067)	(0.0062)	(0.0086)	(0.549)	(0.539)	(0.732)
2021-11	32.6	38.1	26.8	29.6	37.4	22.7
	(0.0066)	(0.0062)	(0.0086)	(0.548)	(0.518)	(0.729)

Notes: The table displays mean and standard errors for the variable working hours by month and gender. The first column shows the average working hours of all working-age (18-55 years old) parents with a child below 16 years old. The second column shows the average working hours for the LISS sample. For all individuals in the LISS sample, which can be linked to the administrative records, we take the actual working hours from the administrative records. For the individuals which cannot be linked, we take the information on working hours from the LISS survey.

Table A.7: Remote working hours over time

	LISS		
	All	Fathers	Mothers
2020-02	4.5	4.8	4.2
	(0.46)	(0.67)	(0.63)
2020-04	17	19	14
	(0.85)	(1.3)	(1.1)
2020-11	14	17	12
	(0.78)	(1.2)	(1)
2021-11	13	14	11
	(0.71)	(1.1)	(0.94)

Notes: The table shows mean and standard errors for the variable remote work hours by month and gender for the LISS sample.

Table A.8: Commuting hours over time

	LISS		
	All	Fathers	Mothers
2019-11	4.6	6	3
	(0.22)	(0.36)	(0.21)
2020-04	1.9	2.1	1.5
	(0.19)	(0.24)	(0.29)
2020-11	2.4	2.9	1.8
	(0.13)	(0.21)	(0.15)
2021-11	2.9	3.6	2.2
	(0.19)	(0.27)	(0.26)

Notes: The table shows mean and standard errors for the variable remote work hours by month and gender for the LISS sample.

Table A.9: Remote work dummy over time

	LISS		
	All	Fathers	Mothers
2020-02	0.34	0.36	0.33
	(0.023)	(0.032)	(0.032)
2020-04	0.61	0.63	0.59
	(0.023)	(0.031)	(0.033)
2020-11	0.55	0.6	0.5
	(0.022)	(0.031)	(0.032)
2021-11	0.54	0.58	0.49
	(0.023)	(0.031)	(0.032)

Notes: The table shows the mean and standard errors of the variable remote work dummy by month and gender for the LISS sample. We construct the remote work dummy ourselves such that it measures whether an individual did any remote work or none at all.

Table A.10: Remote work share over time

	LISS		
	All	Fathers	Mothers
2020-02	0.13	0.12	0.15
	(0.014)	(0.016)	(0.023)
2020-04	0.51	0.51	0.51
	(0.025)	(0.033)	(0.037)
2020-11	0.43	0.45	0.41
	(0.025)	(0.031)	(0.039)
2021-11	0.37	0.37	0.38
	(0.022)	(0.028)	(0.034)

Notes: The table shows mean and standard errors of the the variable remote work share by month and gender for the LISS sample. The remote work share is calculated as hours worked from home divided by total working hours.

Table A.11: Childcare hours over time

	LISS		
	All	Fathers	Mothers
2019-11	23.1	17	28.4
	(0.886)	(0.959)	(1.35)
2020-04	36	30	41.2
	(0.962)	(1.34)	(1.3)
2020-11	22.9	20	25.5
	(0.764)	(1.06)	(1.07)
2021-11	23.1	18.7	27
	(0.758)	(0.96)	(1.1)

Notes: The table shows mean and standard errors for the variable childcare hours by month and gender for the LISS sample.

Appendix B Additional regression results

B.1 Remote work and Commuting

Table B.1: Predictive power of potential remote working hours for realized hours worked from home and commuting time

	Remote working hours		Commuting hours	
	(1)	(2)	(3)	(4)
Constant	5.68***	1.49*	4.63***	4.06***
	(1.25)	(0.79)	(0.28)	(0.38)
2020-04	12.0***	2.61***	−2.7***	−0.95*
	(0.92)	(0.86)	(0.29)	(0.50)
2020-11	9.74***	−0.16	−2.19***	−0.78**
	(0.86)	(0.68)	(0.22)	(0.34)
2021-11	7.92***	0.87	−1.65***	−0.16
	(0.82)	(0.91)	(0.27)	(0.48)
Pot. hours remote work		0.21***		0.04**
		(0.04)		(0.02)
Pot. hours remote work × 2020-04		0.63***		−0.11***
		(0.06)		(0.02)
Pot. hours remote work × 2020-11		0.61***		−0.09***
		(0.05)		(0.02)
Pot. hours remote work × 2021-11		0.42***		−0.09***
		(0.05)		(0.02)
N children == 2	−0.56	−0.4	−0.34	−0.33
	(1.59)	(0.91)	(0.25)	(0.24)
N children == 3	−2.9	−0.93	0.07	−0.03
	(1.82)	(1.06)	(0.36)	(0.34)
N children == 4	−1.68	−0.74	1.66*	1.60*
	(2.59)	(1.96)	(1.01)	(0.96)
N children >4	−4.43	0.57	1.16	0.77
	(3.36)	(1.06)	(1.08)	(0.94)
Age youngest child (std)	−0.2	0.08	0.04*	0.02
	(0.12)	(0.08)	(0.02)	(0.02)
Observations	1,876	1,876	1,876	1,876
R^2	0.081	0.471	0.069	0.11

Notes: Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level. The table displays the relationship between commuting hours and remote work hours and remote work potential. All specification control for age of the youngest child standardized by subtracting the pooled sample mean (6.8) divided by the standard deviation (4.7), as well as indicator variables indicating number of children.. Sample restricted to parents working before the pandemic (Nov 2019).

Table B.2: Predictive power of potential remote working hours for realized hours worked from home and commuting time by gender

	Hrs remote work (1)	Hrs commuting (2)
Constant	1.84	6.06^{***}
	(1.12)	(0.69)
2020-04	3.46^{**}	-2.21^{***}
	(1.45)	(0.83)
2020-11	0.94	-1.73^{***}
	(1.15)	(0.65)
2021-11	0.99	-0.93
	(1.52)	(0.79)
Mother	-0.97	-3.38^{***}
	(1.62)	(0.79)
Mother × 2020-04	-1.4	2.11^{**}
	(1.80)	(0.97)
Mother × 2020-11	-2.02	1.61^{**}
	(1.43)	(0.75)
Mother × 2021-11	-0.14	1.31
	(1.92)	(0.97)
Pot. hours remote work	0.21^{***}	0.00
	(0.04)	(0.02)
Pot. hours remote work × 2020-04	0.62^{***}	-0.09^{***}
	(0.09)	(0.03)
Pot. hours remote work × 2020-11	0.58^{***}	-0.07^{***}
	(0.07)	(0.02)
Pot. hours remote work × 2021-11	0.42^{***}	-0.08^{***}
	(0.07)	(0.03)
Pot. hours remote work × Mother	0.03	0.04
	(0.08)	(0.03)
Pot. hours remote work × Mother × 2020-04	-0.0	-0.01
	(0.12)	(0.04)
Pot. hours remote work × Mother × 2020-11	0.07	-0.01
	(0.10)	(0.03)
Pot. hours remote work × Mother × 2021-11	-0.01	-0.01
	(0.11)	(0.04)
Youngest child age	0-15	0-15
Observations	1,876	1,876
R^2	0.166	0.473

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level. The table displays the relationship between commuting hours and remote work hours and remote work potential interacted with gender. All specification control for the age of the youngest child demeaned by subtracting the pooled sample mean (6.8) interacted with gender, as well as indicator variables indicating number of children. Sample restricted to parents working before the pandemic (Nov 2019).

B.2 Childcare

Table B.3: Hours childcare and potential hours of remote work before and during the CoVid-19 Pandemic – full table

	Childcare Hours	
	(1)	(2)
Constant	28.09***	35.52***
	(1.47)	(1.79)
2020-04	6.80***	6.49***
	(1.43)	(1.41)
2020-11	−4.99***	−5.83***
	(1.27)	(1.28)
2021-11	−3.19***	−3.6***
	(1.19)	(1.20)
Pot. hours remote work	−0.26***	−0.14***
	(0.05)	(0.05)
Pot. hours remote work × 2020-04	0.50***	0.51***
	(0.07)	(0.07)
Pot. hours remote work × 2020-11	0.39***	0.42***
	(0.07)	(0.07)
Pot. hours remote work × 2021-11	0.25***	0.26***
	(0.06)	(0.06)
N children == 2	−0.72	−0.92
	(1.25)	(1.23)
N children == 3	−1.33	−1.49
	(1.52)	(1.49)
N children == 4	−1.23	−1.49
	(2.41)	(2.59)
N children >4	2.05	−0.6
	(2.48)	(2.41)
Age youngest child (std)	−1.92***	−1.88***
	(0.10)	(0.10)
Controlling for Working Hours (2019-11)	No	Yes
Observations	2,234	2,234
R^2	0.273	0.308

Notes: Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level. This table displays for the LISS Sample, how the relationship between remote work ability and childcare changes over the course of the pandemic. All specification control for age of the youngest child demeaned by subtracting the pooled sample mean (6.8), as well as indicator variables indicating number of children. Potential hours of remote work is set to zero for parents who do not work before the pandemic. Column (2) restricts the sample to parents who work 35 hours or more before the pandemic, column (3) restricts the sample to parents working between 20 and 34 hours, and column (4) restricts the sample to parents working less than 20 hours.

Table B.4: Hours spent on childcare and potential hours of remote work before and during the CoVid-19 Pandemic, conditional on working in November 2019

	Childcare Hours	
	(1)	(2)
Constant	25.53***	37.63***
	(1.48)	(2.17)
2020-04	5.45***	5.79***
	(1.65)	(1.62)
2020-11	−6.66***	−6.41***
	(1.34)	(1.33)
2021-11	−5.31***	−5.31***
	(1.33)	(1.32)
Pot. hours remote work	−0.19***	−0.07
	(0.05)	(0.05)
Pot. hours remote work × 2020-04	0.56***	0.55***
	(0.08)	(0.08)
Pot. hours remote work × 2020-11	0.47***	0.46***
	(0.07)	(0.07)
Pot. hours remote work × 2021-11	0.36***	0.36***
	(0.06)	(0.06)
N children == 2	−0.3	−0.78
	(1.28)	(1.25)
N children == 3	−0.04	−0.69
	(1.61)	(1.55)
N children == 4	−0.26	−0.21
	(2.79)	(2.80)
N children >4	5.07*	0.66
	(2.94)	(2.20)
Age youngest child (std)	−1.78***	−1.73***
	(0.11)	(0.11)
Controlling for Working Hours (2019-11)	No	Yes
Observations	1,876	1,876
R^2	0.294	0.332

Notes: Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level. This table displays for the LISS Sample, how the relationship between remote work ability and childcare changes over the course of the pandemic. All specification control for age of the youngest child demeaned by subtracting the pooled sample mean (6.8), as well as indicator variables indicating number of children. Sample restricted to parents working before the pandemic (Nov 2019). Column (2) restricts the sample to parents that work 35 hours or more, column (3) restricts the sample to parents working between 20 and 34 hours, and column (4) restricts the sample to parents working less than 20 hours.

Table B.5: Evolution of the gender care gap and potential hours of remote work – full table

	Hrs childcare		
	(1)	(2)	(3)
Constant	17.28^{***}	18.05^{***}	17.75^{***}
	(1.41)	(1.43)	(1.44)
2020-04	12.8^{***}	10.49^{***}	10.49^{***}
	(1.53)	(1.46)	(1.46)
2020-11	2.96^{**}	1.20	1.69
	(1.29)	(1.29)	(1.26)
2021-11	1.55	0.31	0.36
	(1.19)	(1.20)	(1.23)
N children == 2	0.72	0.73	0.66
	(1.59)	(1.55)	(1.56)
N children == 3	−0.12	0.20	0.21
	(2.07)	(2.03)	(2.04)
N children == 4	1.57	1.58	1.33
	(3.80)	(3.65)	(3.62)
N children >4	5.66	5.35	4.97
	(4.00)	(4.08)	(4.17)
Age youngest child (std)	-1.4^{***}	-1.36^{***}	-1.34^{***}
	(0.14)	(0.14)	(0.14)
Age youngest child (std) × Mother	-1.07^{***}	-1.06^{***}	-1.1^{***}
	(0.18)	(0.18)	(0.18)
N children == 2 × Mother	−2.07	−1.81	−1.99
	(2.13)	(2.17)	(2.17)
N children == 3 × Mother	−1.46	−1.45	−1.66
	(2.66)	(2.64)	(2.67)
N children == 4 × Mother	−4.02	−2.74	−3.02
	(5.07)	(4.99)	(4.95)
N children >4× Mother	-8.18^{*}	−6.48	−6.72
	(4.75)	(4.96)	(5.09)
Mother	14.01^{***}	12.44^{***}	12.67^{***}
	(2.13)	(2.13)	(2.14)
Mother × 2020-04	−0.09	3.85^{**}	3.74^{*}
	(1.99)	(1.94)	(1.94)
Mother × 2020-11	-6.15^{***}	-3.29^{*}	-3.36^{*}
	(1.84)	(1.87)	(1.86)
Mother × 2021-11	-3.31^{**}	−1.46	−1.34
	(1.60)	(1.63)	(1.62)
Pot. hours remote work (std)		-0.16^{***}	-0.1^{**}
		(0.05)	(0.05)
Pot. hours remote work (std) × 2020-04		0.52^{***}	0.55^{***}
		(0.07)	(0.09)
Pot. hours remote work (std) × 2020-1152		0.36^{***}	0.26^{***}
		(0.07)	(0.08)
Pot. hours remote work (std) × 2021-11		0.23^{***}	0.21^{***}
		(0.06)	(0.07)
Pot. hours remote work (std) × Mother			−0.16
			(0.10)

Table B.6: Evolution of the gender care gap and potential hours of remote work – conditional on working in November 2019

	Hrs childcare		
	(1)	(2)	(3)
Constant	16.3***	16.44***	16.41***
	(1.39)	(1.34)	(1.34)
2020-04	13.38***	13.7***	13.75***
	(1.55)	(1.44)	(1.44)
2020-11	3.75***	3.46***	3.50***
	(1.32)	(1.26)	(1.25)
2021-11	2.08*	1.83	1.85
	(1.20)	(1.17)	(1.16)
Mother	12.45***	11.65***	11.71***
	(2.21)	(2.16)	(2.16)
Mother × 2020-04	1.61	2.08	1.92
	(2.11)	(2.00)	(2.02)
Mother × 2020-11	−5.61***	−4.94***	−4.93**
	(1.97)	(1.91)	(1.92)
Mother × 2021-11	−3.09*	−2.76*	−2.77*
	(1.70)	(1.67)	(1.67)
Pot. hours remote work (std)		−0.02	−0.02
		(0.02)	(0.02)
Pot. hours remote work (std) × 2020-04		0.20***	0.22***
		(0.03)	(0.04)
Pot. hours remote work (std) × 2020-11		0.15***	0.13***
		(0.02)	(0.03)
Pot. hours remote work (std) × 2021-11		0.11***	0.10***
		(0.02)	(0.03)
Pot. hours remote work (std) × Mother			−0.0
			(0.03)
Pot. hours remote work (std) × Mother × 2020-04			−0.06
			(0.05)
Pot. hours remote work (std) × Mother × 2020-11			0.04
			(0.04)
Pot. hours remote work (std) × Mother × 2021-11			0.01
			(0.04)
Observations	1,876	1,876	1,876
R^2	0.317	0.369	0.37

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the household level.All specification control for age of the youngest child interacted standardized by subtracting the pooled sample mean (6.8) divided by the standard deviation (4.7) interacted with gender, as well as indicator variables indicating number of children. Sample restricted to parents working before the pandemic (Nov 2019).

B.3 Labor supply: Regression equation with pot. commuting gains

$$\begin{aligned}
\text{Working Hours}_{i,t} = {} & \alpha + \chi \text{ Pot. hrs remote work}_i + \phi \text{ Pot. hrs remote work partner}_i \\
& + \upsilon \text{ Pot. commuting gains}_i + \nu \text{ Pot. commuting gains partner}_i \\
& + \sum_{t=-1}^{2} (\beta_t \text{ Pot. hrs remote work}_i + \delta_t \text{ Pot. hrs remote work partner}_i \\
& + \lambda_t \text{ Pot. commuting gains}_i + \phi_t \text{ Pot. commuting gains partner}_i) \\
& \times \mathbb{1}(Year = t) \\
& + \sum_{t=-1}^{2} (\gamma_t \text{ Pot. hrs remote work}_i + \omega_t \text{ Pot. hrs remote work partner}_i \\
& + \theta_t \text{ Pot. commuting gains}_i + \kappa_t \text{ Pot. commuting gains partner}_i) \\
& \times \mathbb{1}(Year = t) \times \text{Pandemic}_i \\
& + \sum_{t=-1}^{2} \mu_t \mathbb{1}(Year = t) + \sum_{t=-1}^{2} \sigma_t \mathbb{1}(Year = t) \times \text{Pandemic}_i \\
& + \pi \text{ Pandemic}_i + \rho \text{ Age youngest child}_{i,0} + \eta \text{ Number children}_{i,t} \\
& + \iota \text{ Age}_{i,t} + \xi \text{ Age partner}_{i,t} + \epsilon_{i,t}
\end{aligned}$$

B.4 Labor supply

Table B.9: The effect of potential remote hours on working hours

	Mothers		Fathers	
	(1)	(2)	(3)	(4)
Constant	19.823***	21.279***	40.68***	41.274***
	(0.06)	(0.057)	(0.051)	(0.046)
Part: Pot hrs wfh × t = -1 × Pand	0.00	−0.0	−0.002	−0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Part: Pot hrs wfh × t = 1 × Pand	0.008***	0.005**	0.004**	0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Part: Pot hrs wfh × t = 2 × Pand	0.01***	0.005**	0.009***	0.007***
	(0.002)	(0.002)	(0.002)	(0.003)
Pot hrs wfh × t = -1 × Pand	−0.021***	−0.024***	−0.02***	−0.019***
	(0.002)	(0.002)	(0.002)	(0.002)

Pot hrs wfh × t = 1 × Pand	0.051^{***}	0.05^{***}	0.03^{***}	0.026^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Pot hrs wfh × t = 2 × Pand	0.073^{***}	0.061^{***}	0.028^{***}	0.016^{***}
	(0.002)	(0.003)	(0.002)	(0.002)
Part: Pot comm gain × t = -1 × Pand		0.00		0.004^{***}
		(0.001)		(0.001)
Part: Pot comm gain × t = 1 × Pand		0.003^{***}		0.00
		(0.001)		(0.001)
Part: Pot comm gain × t = 2 × Pand		0.004^{**}		0.001
		(0.001)		(0.002)
Pot comm gain × t = -1 × Pand		0.004^{**}		0.004^{***}
		(0.002)		(0.001)
Pot comm gain × t = 1 × Pand		-0.003^{**}		-0.001
		(0.002)		(0.001)
Pot comm gain × t = 2 × Pand		0.006^{***}		0.004^{***}
		(0.002)		(0.001)
t = -1	-0.711^{***}	-0.67^{***}	-0.736^{***}	-0.571^{***}
	(0.009)	(0.011)	(0.01)	(0.011)
t = 1	0.658^{***}	0.564^{***}	0.403^{***}	0.279^{***}
	(0.009)	(0.011)	(0.009)	(0.01)
t = 2	1.158^{***}	0.954^{***}	0.425^{***}	0.209^{***}
	(0.014)	(0.015)	(0.014)	(0.014)
Pand	1.511^{***}	0.782^{***}	0.327^{***}	-0.291^{***}
	(0.023)	(0.022)	(0.022)	(0.022)
t = -1 × Pand	0.461^{***}	0.414^{***}	0.918^{***}	0.75^{***}
	(0.025)	(0.026)	(0.025)	(0.026)
t = 1 × Pand	-0.858^{***}	-0.746^{***}	-0.931^{***}	-0.801^{***}
	(0.025)	(0.026)	(0.026)	(0.026)
t = 2 × Pand	-0.762^{***}	-0.551^{***}	-0.681^{***}	-0.46^{***}
	(0.033)	(0.034)	(0.033)	(0.033)
Pot hrs wfh	0.546^{***}	0.577^{***}	0.056^{***}	0.051^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Pot hrs wfh × Pand	-0.06^{***}	-0.05^{***}	-0.009^{***}	0.01^{***}
	(0.002)	(0.002)	(0.001)	(0.002)
Pot hrs wfh × t = -1	0.02^{***}	0.024^{***}	0.013^{***}	0.01^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Pot hrs wfh × t = 1	-0.029^{***}	-0.03^{***}	-0.01^{***}	-0.008^{***}
	(0.001)	(0.001)	(0.00)	(0.001)
Pot hrs wfh × t = 2	-0.053^{***}	-0.05^{***}	-0.014^{***}	-0.006^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot hrs wfh	-0.028^{***}	-0.03^{***}	-0.1^{***}	-0.104^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot hrs wfh × Pand	-0.001	0.002	-0.002	-0.0

	(0.001)	(0.002)	(0.002)	(0.002)
Part: Pot hrs wfh × t = -1	−0.001	−0.001	0.004***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot hrs wfh × t = 1	0.00	−0.0	−0.001	−0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot hrs wfh × t = 2	−0.001	0.001	−0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot comm gain		0.00		0.006***
		(0.001)		(0.001)
Part: Pot comm gain × Pand		−0.001		−0.003***
		(0.001)		(0.001)
Part: Pot comm gain × t = -1		0.00		−0.0
		(0.00)		(0.001)
Part: Pot comm gain × t = 1		−0.0		0.00
		(0.00)		(0.001)
Part: Pot comm gain × t = 2		−0.001*		−0.002**
		(0.001)		(0.001)
Pot comm gain		−0.055***		−0.013***
		(0.001)		(0.00)
Pot comm gain × Pand		−0.0		−0.004***
		(0.001)		(0.001)
Pot comm gain × t = -1		−0.002***		−0.001***
		(0.001)		(0.00)
Pot comm gain × t = 1		0.006***		0.002***
		(0.001)		(0.00)
Pot comm gain × t = 2		0.004***		−0.0
		(0.001)		(0.00)
N children = 2	−1.0***	−1.106***	0.227***	0.139***
	(0.015)	(0.014)	(0.013)	(0.012)
N children = 3	−2.043***	−2.079***	0.15***	0.099***
	(0.022)	(0.021)	(0.019)	(0.017)
N children = 4	−3.589***	−3.495***	0.104**	0.115***
	(0.052)	(0.05)	(0.043)	(0.039)
N children >4	−6.149***	−6.0***	0.558***	0.552***
	(0.137)	(0.137)	(0.109)	(0.10)
Age	0.00	−0.01***	−0.067***	−0.056***
	(0.002)	(0.002)	(0.002)	(0.002)
Part: Age	0.025***	0.026***	−0.038***	−0.046***
	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.175	0.193	0.015	0.018

Table B.7: The effect of potential remote share on working hours

	Mothers		Fathers	
	(1)	(2)	(3)	(4)
Part: Pot share wfh × t = -1 × Pand	-0.0	-0.0	-0.001^{*}	-0.002^{***}
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot share wfh × t = 1 × Pand	0.004^{***}	0.002^{***}	0.002^{***}	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot share wfh × t = 2 × Pand	0.004^{***}	0.002^{**}	0.003^{***}	0.002^{**}
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot comm gain × t = -1 × Pand		0.001		0.004^{***}
		(0.001)		(0.001)
Part: Pot comm gain × t = 1 × Pand		0.003^{***}		0.00
		(0.001)		(0.001)
Part: Pot comm gain × t = 2 × Pand		0.004^{***}		0.002
		(0.001)		(0.002)
R^2	0.097	0.104	0.01	0.014

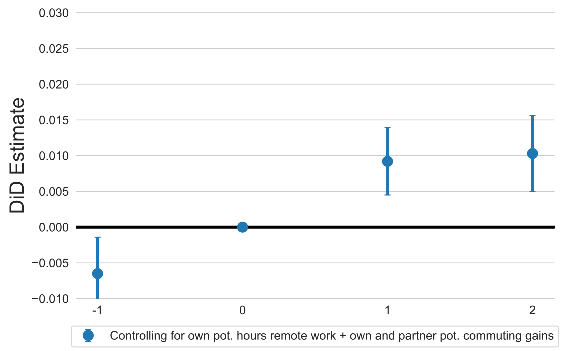
Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Standard errors obtained by clustering on the individual level. Full results in Table B.11.

Table B.11: The effect of potential remote share on working hours

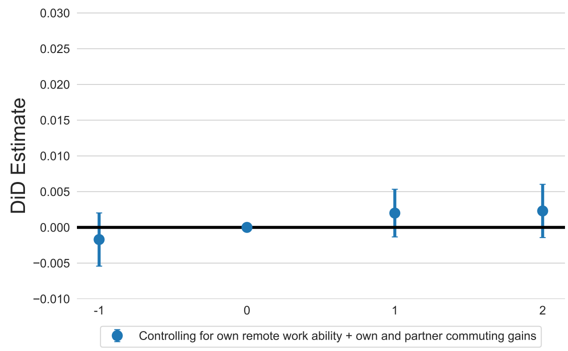
	Mothers		Fathers	
	(1)	(2)	(3)	(4)
Constant	19.523***	21.076***	40.806***	41.421***
	(0.064)	(0.061)	(0.051)	(0.046)
Part: Pot share wfh × t = -1 × Pand	−0.0	−0.0	−0.001*	−0.002***
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot share wfh × t = 1 × Pand	0.004***	0.002***	0.002***	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot share wfh × t = 2 × Pand	0.004***	0.002**	0.003***	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
Pot share wfh × t = -1 × Pand	−0.003***	−0.003***	−0.007***	−0.006***
	(0.001)	(0.001)	(0.001)	(0.001)
Pot share wfh × t = 1 × Pand	0.014***	0.015***	0.011***	0.01***
	(0.001)	(0.001)	(0.001)	(0.001)
Pot share wfh × t = 2 × Pand	0.02***	0.017***	0.01***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Part: Pot comm gain × t = -1 × Pand		0.001		0.004***
		(0.001)		(0.001)
Part: Pot comm gain × t = 1 × Pand		0.003***		0.00
		(0.001)		(0.001)
Part: Pot comm gain × t = 2 × Pand		0.004***		0.002
		(0.001)		(0.002)
Pot comm gain × t = -1 × Pand		−0.001		0.002*
		(0.002)		(0.001)
Pot comm gain × t = 1 × Pand		−0.007***		−0.002**
		(0.002)		(0.001)
Pot comm gain × t = 2 × Pand		−0.0		0.001
		(0.002)		(0.001)
t = -1	−0.724***	−0.669***	−0.772***	−0.59***
	(0.01)	(0.012)	(0.01)	(0.011)
t = 1	0.672***	0.571***	0.404***	0.273***
	(0.01)	(0.011)	(0.009)	(0.011)
t = 2	1.192***	0.98***	0.452***	0.236***
	(0.015)	(0.016)	(0.015)	(0.014)
Pand	1.569***	0.82***	0.392***	−0.213***
	(0.024)	(0.024)	(0.023)	(0.022)
t = -1 × Pand	0.438***	0.378***	0.904***	0.722***
	(0.026)	(0.027)	(0.026)	(0.026)
t = 1 × Pand	−0.899***	−0.784***	−0.933***	−0.799***
	(0.027)	(0.028)	(0.026)	(0.027)

t = 2 × Pand	−0.804***	−0.574***	−0.68***	−0.457***
	(0.035)	(0.036)	(0.034)	(0.034)
Pot share wfh	0.117***	0.112***	−0.002***	−0.009***
	(0.00)	(0.00)	(0.00)	(0.00)
Pot share wfh × Pand	−0.011***	−0.008***	−0.004***	0.001
	(0.001)	(0.001)	(0.00)	(0.00)
Pot share wfh × t = -1	0.003***	0.004***	0.005***	0.004***
	(0.00)	(0.00)	(0.00)	(0.00)
Pot share wfh × t = 1	−0.005***	−0.006***	−0.003***	−0.002***
	(0.00)	(0.00)	(0.00)	(0.00)
Pot share wfh × t = 2	−0.01***	−0.009***	−0.005***	−0.003***
	(0.00)	(0.00)	(0.00)	(0.00)
Part: Pot share wfh	0.005***	0.007***	−0.021***	−0.022***
	(0.00)	(0.00)	(0.00)	(0.00)
Part: Pot share wfh × Pand	−0.002***	−0.001*	−0.003***	−0.001**
	(0.00)	(0.001)	(0.00)	(0.001)
Part: Pot share wfh × t = -1	0.001***	0.001**	0.002***	0.002***
	(0.00)	(0.00)	(0.00)	(0.00)
Part: Pot share wfh × t = 1	−0.001***	−0.001**	−0.001***	−0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Part: Pot share wfh × t = 2	−0.002***	−0.001***	−0.002***	−0.001***
	(0.00)	(0.00)	(0.00)	(0.00)
Part: Pot comm gain		−0.009***		−0.0
		(0.001)		(0.001)
Part: Pot comm gain × Pand		−0.0		−0.002**
		(0.001)		(0.001)
Part: Pot comm gain × t = -1		−0.0		−0.001
		(0.00)		(0.001)
Part: Pot comm gain × t = 1		−0.0		0.00
		(0.001)		(0.001)
Part: Pot comm gain × t = 2		−0.0		−0.001*
		(0.001)		(0.001)
Pot comm gain		0.004***		0.006***
		(0.001)		(0.00)
Pot comm gain × Pand		0.001		−0.001
		(0.001)		(0.001)
Pot comm gain × t = -1		−0.002**		−0.002***
		(0.001)		(0.00)
Pot comm gain × t = 1		0.005***		0.001***
		(0.001)		(0.00)
Pot comm gain × t = 2		0.007***		0.002***
		(0.001)		(0.00)
N children = 2	−1.52***	−1.639***	0.342***	0.253***

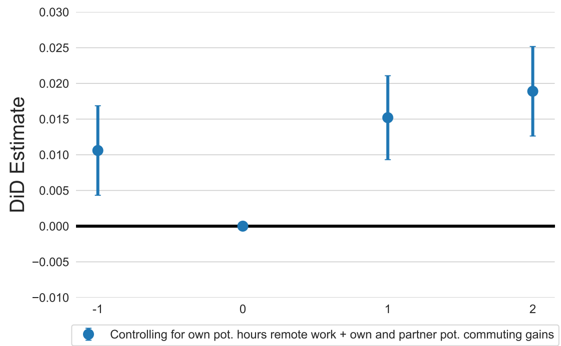
	(0.016)	(0.015)	(0.013)	(0.012)
N children = 3	-2.892^{***}	-2.933^{***}	0.328^{***}	0.274^{***}
	(0.024)	(0.023)	(0.019)	(0.017)
N children = 4	-4.813^{***}	-4.722^{***}	0.271^{***}	0.285^{***}
	(0.057)	(0.056)	(0.043)	(0.04)
N children >4	-7.841^{***}	-7.702^{***}	0.684^{***}	0.694^{***}
	(0.149)	(0.151)	(0.109)	(0.101)
Age	0.044^{***}	0.033^{***}	-0.071^{***}	-0.06^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
Part: Age	0.033^{***}	0.033^{***}	-0.026^{***}	-0.034^{***}
	(0.002)	(0.002)	(0.002)	(0.002)
R^2	0.097	0.104	0.01	0.014



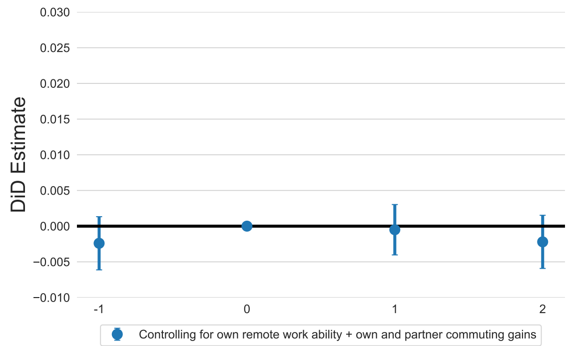
(a) Effect of fathers' potential remote work hours on mothers' working hours, youngest child < 6



(b) Effect of fathers' potential commuting gains on mothers' working hours, youngest child < 6



(c) Effect of mothers' potential remote work hours on fathers' working hours, youngest child < 6



(d) Effect of mothers' potential commuting gains on fathers' working hours, youngest child < 6

Figure B.1: Direct and indirect effect of potential hours of remote work of the partner on own working hours, child below 6

Notes: The figure separates the event-study DiD estimate for the effect of potential hours of remote work of the partner on own working hours in a direct effect through potential hours of remote work and an indirect effect through potential commuting gains. Figures B.1a and B.1c show the event-study DiD estimates for the direct effect of potential hours of remote work of the partner on own working hours relative to the year of the Covid/Placebo shock. Figures B.1b and B.1d show the event-study DiD estimates for the effect through potential commuting gains of the partner on own working hours relative to the year of the Covid/Placebo shock. Results are reported separately for mothers and fathers with a youngest child below 6. The specification includes own and partner potential hours of remote work and own and partner potential commuting gains into the regression. Potential hours of remote work are calculated by multiplying the imputed remote work capability with actual working hours for the periods -1 and 0 and then taking the mean of it. Potential commuting gains are calculated by multiplying the imputed remote work capability with the commuting distance (in km), assuming that all individuals commute the same number of working days per week, for the periods -1 and 0 and then averaging it. All specifications include controls for own and partner age and fixed effects for the age of the youngest child and the number of children. Standard errors are obtained by clustering on the individual level. Complete regression results for mothers can be found in table **??**. Complete regression results for fathers can be found in table **??**.