

von Gaudecker, Hans-Martin; Holler, Radost; Simon, Lenard; Zimpelmann, Christian

Conference Paper

How has the increase in work from home impacted the parental division of labor?

Beiträge zur Jahrestagung des Vereins für Socialpolitik 2023: Growth and the "sociale Frage"

Provided in Cooperation with:

Verein für Socialpolitik / German Economic Association

Suggested Citation: von Gaudecker, Hans-Martin; Holler, Radost; Simon, Lenard; Zimpelmann, Christian (2023) : How has the increase in work from home impacted the parental division of labor?, Beiträge zur Jahrestagung des Vereins für Socialpolitik 2023: Growth and the "sociale Frage", ZBW - Leibniz Information Centre for Economics, Kiel, Hamburg

This Version is available at:

<https://hdl.handle.net/10419/277603>

Standard-Nutzungsbedingungen:

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

Terms of use:

Documents in EconStor may be saved and copied for your personal and scholarly purposes.

You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.

If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.

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}

February 23, 2023

Abstract

In this study, we analyze how the parents of young children react to the change in working conditions during the COVID-19 pandemic using representative panel data from the Netherlands spanning four waves from 2019 to 2021. We find that over the course of the pandemic, fathers increase childcare hours leading to a more egalitarian division of childcare between parents. We show that this change can be fully accounted for by fathers gaining asymmetrically more temporal flexibility through the shift to remote work accelerated by the pandemic. Additionally, we find evidence that mothers whose spouse have remote work possibilities increased their working hours over the course of the pandemic. Our results provide evidence that part of the unequal division of labor within families with respect to market and non-market work is driven by an asymmetric distribution of temporal flexibility. This asymmetry can be the result of joint household optimization when temporal flexibility in jobs is necessary for childcare provision but punished in terms of remuneration. In particular, our results suggest that if remote work becomes more widely accepted by employers, the division of non-market work within households can become more equal in the long term – even without a shift in norms or preferences.

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

JEL Classification: J13, J16, J22

*Radost Holler, Universität Bonn. Email: [holler\[at\]uni-bonn\[dot\]de](mailto:holler[at]uni-bonn[dot]de).

†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. Fathers, on the other hand, typically specialise in market work – potentially driven by non-linear returns to working hours (Bick, Blandin, and Rogerson, 2022; Gicheva, 2013) which make it less attractive for parents to share market and non-market work equally.

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.

In this paper, we exploit the way the CoViD-19 pandemic has evolved in the Netherlands in order to quantify this channel. We do so by using 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. Two thirds of the decline can be attributed to families where fathers' remote working potential was high.

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 strongly 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 between 2013 and 2016. We find that mothers and fathers indeed increase their labor supply in response to their partners' newly gained job flexibility. Given that fathers gained asymmetrically more job flexibility, this in turn means that mothers disproportionately increased their labor supply. We find no evidence that this result is driven by reduced commuting time. Instead, it seems that the increased availability of parents at home drives the results.

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 suggestive 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.

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 the aforementioned literature on gendered patterns of market work and non-market work and their relationship to job flexibility 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. A wealth of papers looks at how couples share the increased childcare burden early in the pandemic while childcare facilities and schools were closed in a wide-range of countries.¹ The 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 led 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

¹A 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; Zamorro 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 sources, sample selection, and basic demographics

Our study is based on customized survey data from the LISS panel, population-wide administrative records from Statistics Netherlands, and both datasets linked at the individual level. We describe both data sources in the following subsections. The last subsection describes the basic socio-demographic characteristics of our sample.

2.1 Customized survey data from the LISS Panel

In our study, we use the Longitudinal Internet Studies for the Social Sciences (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, in the period between mid-March and December 2020, we fielded six questionnaires on the impact that the CoViD-19 pandemic had on peoples' lives. From those surveys, we employ information on remote work potential and on working hours at the point in time just before the pandemic started affecting working lives. The documentation of the entire questionnaires can be found in von Gaudecker, Zimpelmann, et al. (2021). 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.² 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

²The question in December 2020 reads: “What percentage of your normal work can you do while working from home?”

the *potential* for remote work – it would not have occurred to many people that essentially all meetings could be held in virtual formats. The correlation between the measure in May and the measure in December is 0.82.³ Given the high stability of this measure, we take the mean across these two dates for each individual for which we observe both, and the one that is available for those who we observe only once. This maximizes the number of observations for which we have this measure available while at the same time reducing potential measurement error if one believes that the variable is approximately stable across time.

Second, 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.

2.2 Population-wide administrative data, Working Conditions Survey

We access detailed administrative microdata from Statistics Netherlands (CBS) via a secure online environment which we use in our analyses in two ways: First, we obtain more precise measures of household composition and labor supply for our survey sample. Second and more importantly, we can greatly expand our sample for the analysis of labor supply and consider the full population of the Netherlands. 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.

The labor market information is recorded monthly for each individual. To harmonize the CBS data with the LISS data (and for computational feasibility), we extract the labor market information in November of each year from 2013 to 2021. We use actual working hours, which are recorded at the spell level. Spells cover one month in case an employee works the whole month, and shorter than a month in case he or she does not work the whole month. We convert them to weekly hours throughout.

³In the Appendix of Zimpelmann et al. (2021), we discuss the correlation between the answers in May and December as well as the distributions in great details.

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 by sector and education. We then use this information to impute a measure of potential remote work for all individuals in our data. See Appendix A.1 for a more detailed description of the imputation procedure.

Finally, we are able to link our LISS survey data to the CBS data at the individual level. Doing so is possible for all panel members who gave their consent to the linkage, which holds true for around 90% of individuals in our sample. For these respondents, we are able 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.

2.3 Statistics on socio-demographic variables

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. For some of our analyses below, we require information that is missing for a subset of individuals. For example, we can calculate our measure of potential remote working hours in the LISS panel only if people were working just before the pandemic; in the CBS data we do not observe working hours for self-employed individuals. Where applicable, we exclude individuals with data that is missing by construction from our sample. If doing so affects the descriptive statistics shown here, we comment on it.

Table 1 display 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 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

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

	LISS		CBS	
	Fathers	Mothers	Fathers	Mothers
Age	42.56 (6.51)	40.27 (6.42)	41.41 (6.99)	39.0 (6.72)
Age youngest child	6.75 (4.69)	6.85 (4.74)	6.66 (4.83)	6.7 (4.86)
Number of children	2.08 (0.78)	2.03 (0.8)	1.96 (0.8)	1.94 (0.78)
Education: High	0.46 (0.5)	0.47 (0.5)	0.39 (0.49)	0.44 (0.5)
Education: Middle	0.26 (0.44)	0.27 (0.44)	0.29 (0.45)	0.31 (0.46)
Education: Low	0.04 (0.21)	0.03 (0.18)	0.08 (0.27)	0.07 (0.25)
Education: Unknown	0.24 (0.42)	0.23 (0.42)	0.24 (0.42)	0.18 (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.2 for the numbers over time.

in 2021 compared to 2019 and April 2020 (6.3 years vs 7.2 years, see Table A.2a). This will affect the analysis of childcare hours below, where it will be important to control for the age of the youngest child.

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.

Taken together, from 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.

3.1 The CoViD-19 pandemic in the Netherlands

From March 2020 until the end of 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 highlight the policy environment that was effective in and around the months of our data collection: November 2019, April 2020, November 2020, and November 2021. 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. We describe some key features relevant for our analysis; see Zimpelmann et al. (2021) for a more detailed description with a focus on labor market issues during the first year of the pandemic.

Figure 1 shows the timeline of relevant government policy measures at the points in time for which we have data. 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. However, others like stores for clothes or utilities remained open as long as they were able to maintain the social distancing rules. Public locations were accessible and the use of public transportation was possible.



Figure 1: 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 only 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. In the late spring and summer of 2020, policy makers made it very clear that schools and childcare facilities would be the last institutions to close again 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 restriction. 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. In turn, rather few people became unemployed or dropped out of the labor force; dependent employees did not see their incomes drop (Zimpelmann et al., 2021). Figure 1 shows that the unemployment rate was low throughout the 2019–2021 period. While it was slightly higher in November 2020 than in November 2019, it fell well below these levels in November 2021.

Throughout the part of our sample period that coincides with the CoViD-19 pandemic, the government strongly encouraged remote work.

3.2 Market and non-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.

Table 2 contains the labor market status for our sample of parents for the months of November in the 2016–2021 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 23% to 19%; the unemployed share decreased from 3% to 0.9%.⁴ In the bottom panel, we also see the same trend for fathers, albeit at lower levels. The fraction outside the labor force went from 10.5% to 9.3%; the fraction of unemployed fathers decreased from 2.5% to 0.7%.

Hence, when it comes to the extensive margin, trends of increasing employment of parents continued or even accelerated during pandemic's first two years. Comparing the numbers with aggregate employment trends, parents experienced only a negligible uptick in unemployment/inactivity during 2020; they were thus less affected than the rest of the population. This may partly be explained by the type of jobs (e.g., relatively few parents work in the catering sector). Importantly for our purposes—and in stark contrast to countries where schools and daycare facilities were closed for prolonged periods of time (e.g. Heggeness and Suri, 2021)—there is no evidence that parents dropped out of the labor force to take care of their children.

The share of self-employed parents was high and increased over our observation period. For mothers, it started at 9.3% and gradually went up to 11.8% in late 2021. Among fathers, it increased from 15.1% to 17.7%. For mothers, the rise accounts for half of the decrease in the share of mothers who are not working. For fathers, the rise accounts for the entire decrease.

⁴Note 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 2: Labor market status over time

		Out of the labor force	Unemployed	Self-employed	Part-time employed	Full-time employed
Mothers	2016	0.232	0.030	0.093	0.555	0.092
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	2017	0.226	0.018	0.097	0.568	0.092
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	2018	0.214	0.013	0.101	0.576	0.097
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	2019	0.206	0.012	0.107	0.576	0.099
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
2020	0.203	0.013	0.113	0.568	0.106	
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	
2021	0.189	0.009	0.118	0.568	0.117	
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	
Fathers	2016	0.103	0.025	0.151	0.092	0.631
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	2017	0.106	0.014	0.154	0.100	0.628
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	2018	0.102	0.010	0.160	0.104	0.626
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
	2019	0.099	0.009	0.168	0.108	0.617
		(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
2020	0.099	0.011	0.173	0.108	0.610	
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	
2021	0.093	0.007	0.177	0.111	0.613	
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	

Notes: The table shows the labor market participation for a 20 % sample of all working-age (18-55 years old) parents 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.

Mothers' part time employment went up from 55.5% in 2016 to peak at 57.6% in 2019, and then decreased again to 56.8%. 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 25.3 in 2016 to 26.1 in 2019. This trend accelerated during the pandemic and by 2021, mothers worked 27 hours on average (all numbers referred to in this paragraph are in Appendix Table A.5). Among fathers, average working hours declined slightly from 38.6 in 2016 to 38.4 in 2019 and further to 38.3 at the end of our sample period.

Women take on a much larger share of childcare work than men. Figure 2a displays the evolution of childcare provision by fathers and mothers controlling for changes in household composition over time.⁵ It shows that before the pandemic, mothers on average spent 29.6 hours per week providing care for their children. Fathers' childcare hours, with units depicted on the right axis, were well below that at 18.1 hours. The location of both lines is normalized so they visually start at the same level. This normalization makes the evolution during the pandemic 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.⁶ The large increase in April 2020 was distributed about equally among both genders.

When school and childcare facilities were reopened, total childcare provision recovered to pre-pandemic levels but now with mothers doing approximately 3 hours less, and fathers doing about 3 hours more childcare in November 2020 as compared to November 2019. Towards November 2021, mothers increase their childcare provision again by one and a half hours while

⁵As previously mentioned we have a slight unbalancedness across time in the age of the youngest child in the LISS sample with parents in newer waves having on average younger children than those in older waves. To take out this variation we present results controlling for the (standardized) age of the youngest child and the number of children. Raw averages can be found in Table A.10.

⁶This was the most relevant difference for essential workers, hence we do not mention them elsewhere. See Zimpelmann et al. (2021) for a more detailed analysis of essential worker status.

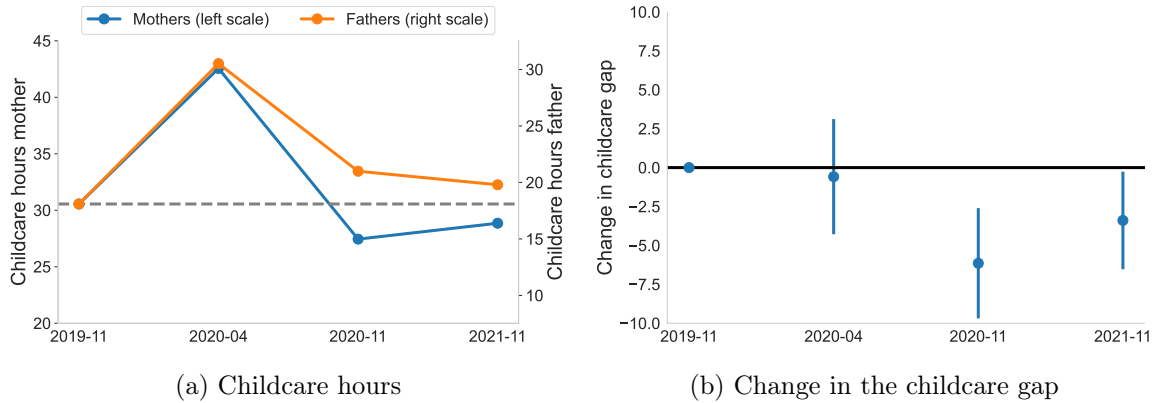


Figure 2: Evolution of the childcare gap 2019–2021.

Notes: Figure 2a shows the development of childcare hours by mothers and fathers in the LISS time use data. Figure 2b shows the development of differences in childcare provision between fathers and mothers. Both are 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 5.

fathers decrease their childcare provision by approximately 1.3 hours as opposed to November 2020.

A different way to look at it is to consider the gap between genders directly. Figure 2b visualizes the result of this exercise, showing that the gender differences we described in the previous paragraphs are very robust in statistical terms. Normalizing the difference between mothers’ and fathers’ childcare provision to its pre-pandemic level, there virtually was no change 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 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.

3.3 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 32% of individuals reported to have performed *some* work from home (see Appendix Table A.6), the hours are very limited. Figure 3a reveals that on average, they are below five for mothers and fathers with fathers' remote hours being about 50 % higher than mothers'. Fathers on average spent almost 6 hours per week commuting to work; mothers spent about 2.5 (Figure 3b).

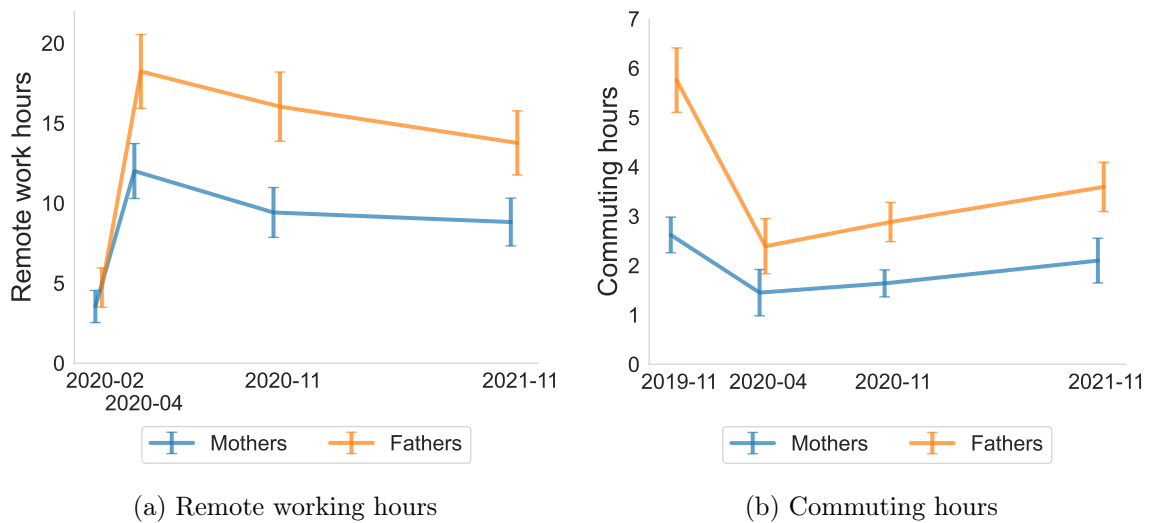


Figure 3: Realized work from home and commuting over time

Notes: Figure 3a displays average remote working hours in the LISS sample over time and by gender. Figure 3b displays average commuting hours in the LISS sample over time and by gender. For underlying numbers see Tables A.8 and A.9. Additionally, Table A.6 contains the evolution over time and by gender of a variable measuring *any* remote work and Table A.7 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 parents of both genders. In April 2020, weekly hours worked from home increased to 12 among mothers and 18 among fathers. Put differently, about fifty percent of actual hours were done from home. Commuting time dropped to 1.5 hours for mothers and 2.4 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.

These large differences prompt us to investigate the *potential* remote working hours. We argue that the capacity to work from home is roughly constant over the 2019-2021 period, but the extent to which this potential was realized changed due to the pandemic. Figure 4a shows

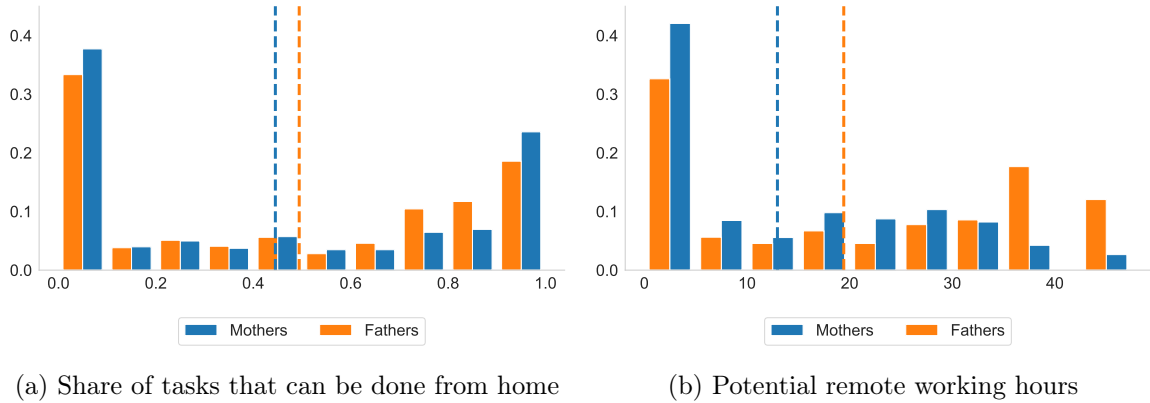


Figure 4: Remote working potential by gender

Notes: Figure 4a displays the distribution of the variable “share of tasks that can be done from home” by gender in the LISS sample. The vertical dashed lines display the mean by gender. Figure 4b 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. The vertical dashed lines display the mean by gender. Samples conditional on working before the pandemic. Similar graphs for the CBS and NEA data are relegated to the Appendix, Figure A.5.

the density of the reported share of tasks that can be done from home by gender in the LISS data, using the variable described in Section 2.1. The distribution is very polarized with the largest share of jobs admitting no remote work at all (37.7% among mothers and 33.3% among fathers). Fathers are also more likely to work in jobs where more than 50% of tasks can be done from home (48.1% vs. 43.9%). Overall, the mean for mothers is 44.8% and for fathers 48.3%. Adams-Prassl et al. (2022) ask a very similar question in two online surveys in the US and UK. Although their samples are not directly comparable to ours (in particular, they are not restricted on parents), it is reassuring that the means are very comparable with 43% in the US and 41% in the UK. Adams-Prassl et al. (2022) show that the individual measure of remote work ability is strongly related to occupations and sectors, but there is also substantial heterogeneity within sectors. This motivates that we use the, potentially more accurate, individual measure for our childcare analyses below.

The overall potential gain in flexibility because of remote work is even larger for men because they work more hours. Figure 4b shows the distribution of potential remote working hours, which are obtained by multiplying the share of potential remote work from Figure 4a with the working hours just before the pandemic. More than 30% of fathers can work at least 30 hours

from home, while only 15% of mothers can do so. The averages are 18.9 and 13.1 weekly hours, respectively.

The explanatory power of potential remote working hours for actual remote working hours is high and it increased dramatically during the pandemic. Column (1) of Table 3 shows that time dummies and family characteristics alone can explain about 8% of the variation in realized remote working hours. The R^2 increases to 0.46 when adding the remote work ability interacted with the time dummies. The coefficient on potential remote working hours increases from 0.2 before the pandemic to 0.8 during its first year. That is, before the pandemic an hour of remote work potential translated into 12 minutes of actual remote work. During the initial lockdown, 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).

Columns (3) and (4) of Table 3 reveal a similar pattern for realized commuting time as the dependent variable. Adding the interaction of potential remote working hours and time dummies leads to an increase in the R^2 by 60%. 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.

Table 3 contains a very simple specification, not differentiating by gender. Adding the full set of interactions with gender in Table B.2 does not reveal any gender differences in the take-up of remote work given equal remote work potential.

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 during the pandemic, from approximately 2.7 hours in late 2019 to 16 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

Table 3: 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	5.15*** (1.16)	1.16 (0.76)	4.64*** (0.27)	4.05*** (0.37)
2020-04	11.81*** (0.87)	2.71*** (0.87)	-2.66*** (0.28)	-0.92* (0.49)
2020-11	9.54*** (0.82)	0.01 (0.72)	-2.26*** (0.22)	-0.82** (0.33)
2021-11	7.09*** (0.74)	0.43 (0.74)	-1.6*** (0.26)	-0.17 (0.46)
Pot. hours remote work		0.21*** (0.04)		0.04** (0.02)
Pot. hours remote work \times 2020-04		0.61*** (0.06)		-0.11*** (0.02)
Pot. hours remote work \times 2020-11		0.60*** (0.05)		-0.09*** (0.02)
Pot. hours remote work \times 2021-11		0.41*** (0.05)		-0.09*** (0.02)
Observations	1,876	1,876	1,876	1,876
R^2	0.078	0.462	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.

works remotely strongly depends on the sector he or she works in.⁷ 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.

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.

⁷Details are in Appendix Section A.1.

4 Results

Our main results establish that the trend towards a more equal division of childcare during the pandemic was entirely driven by households who gained flexibility because 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 had no effect on the hours spent on childcare before the pandemic and that this relationship changed dramatically with 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 3.2.

Table 4 illuminates the relationship between hours of childcare among parents pooled across gender. We include non-working parents by setting their potential hours of remote work to zero.⁸ Column (1) displays the results when pooling across all working hours (including non-working). It shows a significant negative relationship between the potential hours of remote work and hours of childcare provision in November 2019.

Columns (2), (3) and (4) of Table 4 contain results of the same regression when splitting up the sample by hours of work prior to the pandemic. We use three bins: Full-time work (35 working hours or more), part-time work (between 20 and 34 working hours), and short hours (less than 20 working hours) or no work at all. Within these bins, potential remote working hours show only a slightly negative and statistically insignificant relationship to hours of childcare provision prior to the pandemic. Hence, the ability to work from home was unrelated to how much childcare a parent took over for a given level of working hours. This is not surprising as only a tiny fraction of remote work potential was realized.

Mirroring the effect of potential remote work hours on commuting and actual hours of remote work, this drastically changes with the onset of the pandemic. In April 2020, during the first

⁸We report results only including parents who worked before the pandemic in Appendix Table B.4, results do not change. We prefer the sample in Table 4 because when we condition on a parent working before the pandemic, we disproportionately drop mothers, leaving fathers in single-earner households in the sample. Conceptually, we prefer to avoid this imbalance.

Table 4: Childcare hours and potential remote working hours before and during the CoVid-19 Pandemic

	Childcare hours			
	(1)	(2)	(3)	(4)
Constant	28.22*** (1.43)	19.56*** (1.69)	27.34*** (2.72)	37.79*** (2.88)
2020-04	6.20*** (1.40)	6.69*** (2.14)	10.93*** (2.22)	0.38 (2.35)
2020-11	-4.78*** (1.30)	1.52 (1.80)	-3.84* (2.05)	-13.24*** (2.34)
2021-11	-3.19*** (1.21)	-0.51 (1.75)	0.06 (2.07)	-10.1*** (2.12)
Pot. hours remote work	-0.26*** (0.05)	-0.04 (0.05)	-0.13 (0.09)	-0.07 (0.49)
Pot. hours remote work \times 2020-04	0.49*** (0.07)	0.46*** (0.09)	0.35** (0.14)	1.78*** (0.44)
Pot. hours remote work \times 2020-11	0.38*** (0.07)	0.21** (0.08)	0.28** (0.13)	1.14* (0.62)
Pot. hours remote work \times 2021-11	0.26*** (0.06)	0.19*** (0.07)	0.12 (0.13)	0.74 (0.52)
Working hours (2019-11)	All	>34	20-34	<20
Observations	2,234	1,010	706	518
R^2	0.273	0.245	0.375	0.359

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors obtained by clustering on the household level. Baseline month is November 2019. 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. 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 pre-CoVid. The latter includes non-working which are assigned 0 hours of remote work potential. Results of the same regressions when restricting the sample to working parents are included in Appendix Table B.4. The full table is available in Appendix Table B.3

lockdown in which childcare facilities and schools were closed, the relationship turns positive. One hour of potential remote work translates into almost half an hour of childcare for full-time working parents, one fifth of an hour for part-time working parents, and more than an hour for parents who only work little before the pandemic. In November 2020, when childcare facilities and schools were open again, the relationship becomes somewhat weaker but stays strong for full-time working parents. Every hour of remote work potential translates into approximately a quarter of an hour of childcare. This effect remains stable until November 2021. For parents working part-time before the pandemic, the effect becomes weaker and statistically indistinguishable from its pre-pandemic value in November 2021. One reason for this might be that some parents with low working hours and high remote work potential increased their working hours during the pandemic, an effect we shall investigate in the next section.

Table 5 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 2b, which plotted the coefficients on the indicator variables for mother by time period during the pandemic. 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 provision with similar magnitudes. There is a sharp decline (six hours) in the gender gap in childcare in November 2020 accompanied by decrease in childcare provision by mothers and an increase by fathers. The decrease 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, we just established that before the pandemic, potential hours of remote work are negatively related with childcare hours or unrelated, depending on whether we control for working hour bins or not. This makes sense, as 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. Note that none

Table 5: The effect of potential remote working hours on the evolution of the gender care gap

	Childcare hours		
	(1)	(2)	(3)
Constant	18.09*** (1.17)	18.84*** (1.23)	17.88*** (1.41)
2020-04	12.43*** (1.46)	10.33*** (1.42)	10.36*** (1.43)
2020-11	2.90** (1.28)	1.20 (1.29)	1.72 (1.27)
2021-11	1.70 (1.13)	0.39 (1.15)	0.53 (1.18)
Mother	12.46*** (1.31)	11.11*** (1.34)	12.51*** (2.09)
Mother \times 2020-04	-0.43 (1.94)	3.16 (1.92)	3.05 (1.93)
Mother \times 2020-11	-6.01*** (1.84)	-3.24* (1.86)	-3.33* (1.85)
Mother \times 2021-11	-3.4** (1.63)	-1.41 (1.66)	-1.38 (1.65)
Pot. hours remote work (std)		-2.34*** (0.68)	-1.49** (0.73)
Pot. hours remote work (std) \times 2020-04		7.27*** (1.04)	7.56*** (1.31)
Pot. hours remote work (std) \times 2020-11		5.06*** (1.01)	3.57*** (1.18)
Pot. hours remote work (std) \times 2021-11		3.56*** (0.88)	3.16*** (0.99)
Pot. hours remote work (std) \times Mother \times 2020-04			-0.66 (2.02)
Pot. hours remote work (std) \times Mother \times 2020-11			3.73** (1.86)
Pot. hours remote work (std) \times Mother \times 2021-11			1.04 (1.89)
Observations	2,234	2,234	2,234
R^2	0.326	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 (5), 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.

of our results is driven by the fact that we use potential remote working *hours* as a measure for the flexibility gains; everything also goes through if we use the share instead.

In column (2) of Table 5, 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.⁹ Including the standardized potential hours of remote work in the regression 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 thus 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

⁹Defined as potential hrs remote work (std) = $\frac{(\text{potential hrs remote work} - \mu)}{\sigma}$ with the sample mean $\mu = 12,1$ and standard deviation $\sigma = 14,7$.

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 recur to the CBS data, where we have information on hours worked as well.

To estimate the effects of remote work on labor supply, we apply a similar empirical strategy like in the childcare section. We apply a Diff-in-Diff design where the remote work potential two years ago determines the treatment intensity. The idea is to analyse how working hours differ over time for couples having the same number of children, having a youngest child of the same age, and having the same age structure, but different remote work potential.

We estimate the following equation:

$$\begin{aligned}
 (1) \quad \text{Working Hours}_{i,t} = & \alpha + \sum_{t=2018}^{2021} (\beta_t \text{ Pot. hrs remote work}_{i,t-2} + \delta_t \text{ Pot. hrs remote work partner}_{i,t-2}) \\
 & \times \mathbf{1}(\text{Year} = t) + \sum_{t=2018}^{2022} \mu_t \mathbf{1}(\text{Year} = t) \\
 & + \rho \text{ Age youngest child}_{i,t} + \eta \text{ Number children}_{i,t} \\
 & + \iota \text{ Age}_{i,t} + \xi \text{ Age partner}_{i,t} + \epsilon_{i,t}
 \end{aligned}$$

Our dependent variable are unconditional working hours. Factually, this applies only to $t \in \{2020, 2021\}$, because we need individuals to be working in the earlier years to obtain a measure of remote work ability in the administrative data (see Section 2.2 and, for all details, Appendix A.1). We expect that before the Pandemic, the extent of past remote work potential should not differently affect working hours, as the remote work potential was barely realized before the Pandemic (See Table 3).

The time index t measures time relative to just before the (placebo) pandemic – it is 0 in 2019 and 2014, respectively. Our dependent variable are unconditional working hours. Factually, this applies only to $t \in \{1, 2\}$, because we individuals to be working in the earlier years to obtain a measure of remote work ability in the administrative data (see Section 2.2 and, for all details, Appendix A.1).

Of course, we also rely on the assumption that no other attributes of the CoVid-19 pandemic are correlated with potential remote work hours of my partner as well as my subsequent labor supply conditionally on own remote work potential, number of children, age and partners age. The most likely confounder is that the economic shock induced by the CoVid-19 pandemic differentially affected workers depending on their ability to work remotely. Zimpelmann et al. (2021) show that individuals who have a higher remote work capability decrease their working hours less, early in the pandemic in the Netherlands. That is, they experience less of a labor market shock and work more than those with a lower remote work capability which means they are less available for childcare. This, however, should dampen the effect of partner’s remote work capability on own labor supply of parents which implies that, if anything, we may underestimate the effect.

Our coefficients of interest are ω_1 and ω_2 , which measure how the effect of the partners’ potential hours of remote work on working hours has evolved differently across the two time periods for members of households with identical characteristics.

Figures 5a and 5b show our estimates, namely the difference in the effect of partners’ potential hours of remote between CoVid-19 and Placebo sample relative to baseline period 0, over time. We estimate the effects separately for mothers and for fathers. The blue coefficients show the estimates when setting all β_t and γ_t to zero, i.e. when leaving own potential hours remote work out of the regression equation; the orange coefficients additionally control for own potential hours of remote work. Without controlling for own remote work ability, we see a slight negative pre-trend. When controlling for own potential remote work hours, this effect disappears and the pre-trend is insignificant and virtually zero numerical terms. For mothers we find that in both specifications, the DiD estimate is around 0.01, while for fathers the estimates range between 0.01 and 0.02. For illustration, a coefficient of 0.01 implies that for a level of partners’ potential hours of remote work of 12, which is around the average of the fathers’ potential hours of remote work in our sample, the shift towards remote work leads, on average, to around 0.12 working hours more.

To be able to disentangle the effect of the partners’ remote work into a direct effect of increased potential hours of remote work and an indirect effect through potential commuting gains, we further include own and partner potential commuting gains into the regression.¹⁰ Potential

¹⁰The exact regression equation can be found in Appendix B.3.

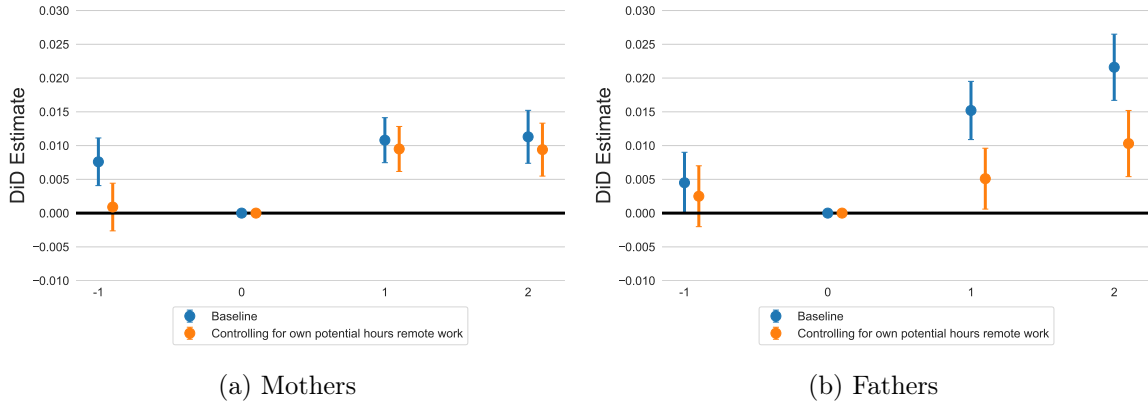


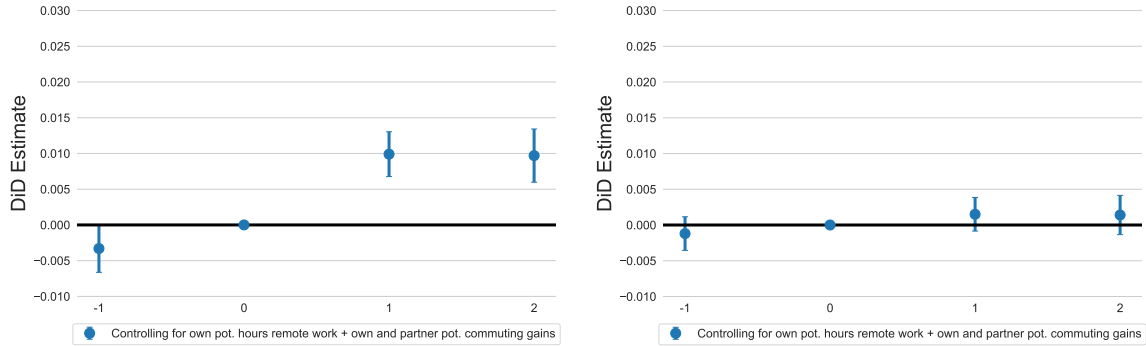
Figure 5: Effect of potential hours of remote work of the partner on own working hours

Notes: The figure displays the event-study DiD estimates for the effect of the potential hours of remote work of the partner on own working hours relative to the year of the Covid/Placebo shock. Results are reported separately for all mothers and fathers. The baseline specification only includes potential hours of remote work of the partner, while the controlling for own potential hours of remote work specification also controls for own potential hours of remote work. 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. 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 can be found for mothers in table B.7 and for fathers in table B.9. The baseline specification can be found in column (1), while the controlling for own potential hours of remote work specification can be found in column (2).

commuting gains are calculated by multiplying the imputed remote work capability with the commuting distance (in km) for the periods -1 and 0 and then averaging it. This implicitly assumes that all individuals commute the same number of working days per week in the absence of the shift to remote work.

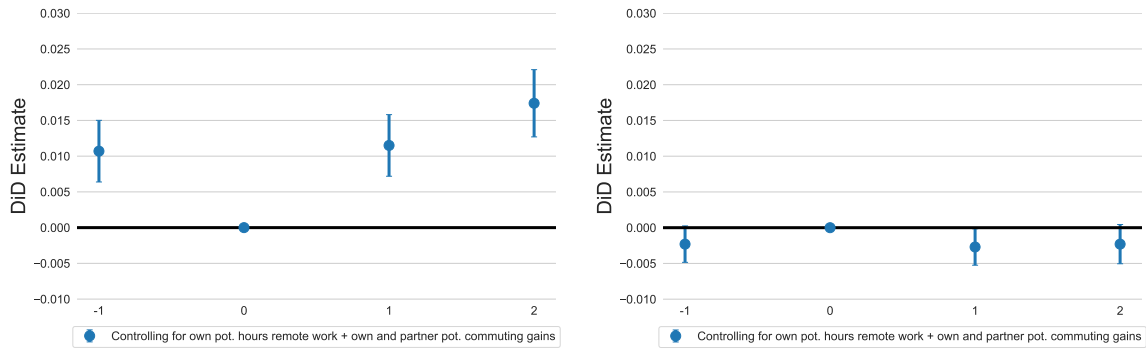
We separate the effect of potential hours of remote work into a direct effect in Figures A.2b and an indirect effect through potential commuting gains in Figure A.2c for mothers. Figure A.2c shows that potential commuting gains do not seem to have explanatory power and that the results come from the direct effect of potential hours of remote work as shown in Figure A.2b.

Figure A.2d and Figure A.2a show the equivalent for fathers. Figure A.2a shows that potential commuting gains do not seem to have explanatory power. However, for the direct effect of potential hours of remote work as shown in Figure A.2d the parallel trend assumption seems to be potentially violated, so that one should not overinterpret the effect size.



(a) Effect of fathers' potential hours of remote work on mothers' working hours

(b) Effect of fathers' potential commuting gains on mothers' working hours



(c) Effect of mothers' potential hours of remote work on fathers' working hours

(d) Effect of mothers' potential commuting gains on fathers' working hours

Figure 6: Direct and indirect effect of potential hours of remote work of the partner on own working hours

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 A.2b and A.2d 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 A.2c and A.2a 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 all mothers and fathers. 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 column (3) of table B.7. Complete regression results for fathers can be found in column (3) of table B.9.

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 was high. The partner’s potential remote work also helps to explain the trend towards mothers working longer hours, which was 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.

References

Adams-Prassl, Abi (2021). “The Gender Wage Gap in an Online Labour Market: The Cost of Interruptions”. In: *Oxford Department of Economics Discussion Paper Series* 944. ISSN: 1471-0498.

- Adams-Prassl, Abi, Teodora Boneva, Marta Golin, and Christopher Rauh (Jan. 1, 2022). “Work That Can Be Done from Home: Evidence on Variation within and across Occupations and Industries”. In: *Labour Economics* 74, p. 102083. ISSN: 0927-5371. DOI: 10.1016/j.labeco.2021.102083. URL: <https://www.sciencedirect.com/science/article/pii/S0927537121001184> (visited on 12/15/2022).
- Alon, Titan, Sena Coskun, Matthias Doepke, David Koll, and Michèle Tertilt (May 2022). “From Mancession to Shecession: Women’s Employment in Regular and Pandemic Recessions”. In: *NBER Macroeconomics Annual 2021* 36.
- Andrew, Alison, Sarah Cattan, Monica Costa Dias, Christine Farquharson, Lucy Kraftman, Sonya Krutikova, Angus Phimister, and Almudena Sevilla (July 2020). *The Gendered Division of Paid and Domestic Work under Lockdown*. IZA Discussion Paper 13500. Institute of Labor Economics (IZA). URL: <https://econpapers.repec.org/paper/izaizadps/dp13500.htm> (visited on 08/31/2020).
- Bang, Minji (2021). “Job Flexibility and Household Labor Supply: Understanding Gender Gaps and the Child Wage Penalty”. In: p. 53.
- Been, J. and Centerdata (Nov. 2021). *LISS Panel - Time Use and Consumption - Part 9*. DANS/KNAW. DOI: 10.17026/DANS-2CV-VZ2C. URL: <https://doi.org/10.17026/dans-2cv-vz2c>.
- Bick, Alexander, Adam Blandin, and Richard Rogerson (Aug. 1, 2022). “Hours and Wages*”. In: *The Quarterly Journal of Economics* 137.3, pp. 1901–1962. ISSN: 0033-5533. DOI: 10.1093/qje/qjac005. URL: <https://doi.org/10.1093/qje/qjac005> (visited on 10/27/2022).
- Bick, Alexander, Bettina Brüggemann, and Nicola Fuchs-Schündeln (2019). “Hours Worked in Europe and the United States: New Data, New Answers”. In: *The Scandinavian Journal of Economics* 121.4, pp. 1381–1416. ISSN: 1467-9442. DOI: 10.1111/sjoe.12344. URL: <https://onlinelibrary.wiley.com/doi/abs/10.1111/sjoe.12344> (visited on 09/13/2020).
- Cortés, Patricia and Jessica Pan (Apr. 2019). “When Time Binds: Substitutes for Household Production, Returns to Working Long Hours, and the Skilled Gender Wage Gap”. In: *Journal of Labor Economics* 37.2, pp. 351–398. ISSN: 0734-306X. DOI: 10.1086/700185.

- URL: <https://www.journals.uchicago.edu/doi/abs/10.1086/700185> (visited on 12/16/2022).
- Del Boca, Daniela, Noemi Oggero, Paola Profeta, and Mariacristina Rossi (Dec. 1, 2020). “Women’s and Men’s Work, Housework and Childcare, before and during COVID-19”. In: *Review of Economics of the Household* 18.4, pp. 1001–1017. ISSN: 1573-7152. DOI: 10.1007/s11150-020-09502-1. URL: <https://doi.org/10.1007/s11150-020-09502-1> (visited on 10/13/2022).
- Farré, Lúdia, Yarine Fawaz, Libertad González, and Jennifer Graves (July 2020). “How the COVID-19 Lockdown Affected Gender Inequality in Paid and Unpaid Work in Spain”. Working Paper. URL: <https://covid-19.iza.org/publications/dp13434/>.
- Felfe, Christina (Jan. 1, 2012). “The Motherhood Wage Gap: What about Job Amenities?”. In: *Labour Economics* 19.1, pp. 59–67. ISSN: 0927-5371. DOI: 10.1016/j.labeco.2011.06.016. URL: <https://www.sciencedirect.com/science/article/pii/S0927537111000777> (visited on 12/16/2022).
- Gicheva, Dora (Oct. 2013). “Working Long Hours and Early Career Outcomes in the High-End Labor Market”. In: *Journal of Labor Economics* 31.4, pp. 785–824. ISSN: 0734-306X, 1537-5307. DOI: 10.1086/669971. URL: <https://www.journals.uchicago.edu/doi/10.1086/669971> (visited on 10/27/2022).
- Goldin, Claudia (Apr. 1, 2014). “A Grand Gender Convergence: Its Last Chapter”. In: *American Economic Review* 104.4, pp. 1091–1119. ISSN: 0002-8282. DOI: 10.1257/aer.104.4.1091.
- Hank, Karsten and Anja Steinbach (2020). “The Virus Changed Everything , Didn’t It ? Couples’ Division of Housework and Childcare before and during the Corona Crisis”. In: *Journal of Family Research*, pp. 1–16. DOI: 10.20377/jfr-488.
- Heggeness, Misty and Palak Suri (Oct. 28, 2021). *Telework, Childcare, and Mothers’ Labor Supply*. preprint. Institute Working Paper. DOI: 10.21034/iwp.52. URL: <https://www.minneapolisfed.org/research/institute-working-papers/telework-childcare-and-mothers-labor-supply> (visited on 01/20/2022).

- Houghton, Kendall (2020). “Childcare and the New Part-Time: Gender Gaps in Long-Hour Professions”. In: p. 40.
- Jessen, Jonas, C. Katharina Spiess, Sevrin Waights, and Katharina Wrohlich (July 28, 2022). “The Gender Division of Unpaid Care Work throughout the COVID-19 Pandemic in Germany”. In: *German Economic Review*. ISSN: 1468-0475. DOI: 10.1515/ger-2022-0003. URL: <https://www.degruyter.com/document/doi/10.1515/ger-2022-0003/html> (visited on 08/24/2022).
- Le Barbanchon, Thomas, Roland Rathelot, and Alexandra Roulet (Feb. 2021). “Gender Differences in Job Search: Trading off Commute against Wage”. In: *The Quarterly Journal of Economics* 136.1, pp. 381–426. DOI: 10.1093/qje/qjaa033.
- Magda, Iga and Katarzyna Lipowska (2021). “Flexibility of Working Time Arrangements and Female Labor Market Outcome”. In: p. 20.
- Mangiavacchi, Lucia, Luca Piccoli, and Luca Pieroni (Aug. 2021). “Fathers Matter: Intra-household Responsibilities and Children’s Wellbeing during the COVID-19 Lockdown in Italy”. In: *Economics & Human Biology* 42, p. 101016. ISSN: 1570677X. DOI: 10.1016/j.ehb.2021.101016. URL: <https://linkinghub.elsevier.com/retrieve/pii/S1570677X2100040X> (visited on 01/20/2022).
- Mas, Alexandre and Amanda Pallais (2017). “Valuing Alternative Work Arrangements”. In: *American Economic Review* 107.12, pp. 3722–59.
- Meekes, Jordy and Wolter H. J. Hassink (May 1, 2022). “Gender Differences in Job Flexibility: Commutes and Working Hours after Job Loss”. In: *Journal of Urban Economics* 129, p. 103425. ISSN: 0094-1190. DOI: 10.1016/j.jue.2022.103425. URL: <https://www.sciencedirect.com/science/article/pii/S009411902200002X> (visited on 10/14/2022).
- Meekes, Jordy, Wolter H. J. Hassink, and Guyonne Kalb (Nov. 2020). “Essential Work and Emergency Childcare: Identifying Gender Differences in COVID-19 Effects on Labour Demand and Supply”. Working Paper. URL: <https://econpapers.repec.org/paper/izaizadps/dp13843.htm> (visited on 01/21/2021).

- Pabilonia, Sabrina and Victoria Vernon (Feb. 25, 2022). *Who Is Doing the Chores and Childcare in Dual-earner Couples during the COVID-19 Era of Working from Home?* Zenodo. DOI: 10.5281/ZENODO.6282646. URL: <https://zenodo.org/record/6282646> (visited on 03/16/2022).
- Sevilla, Almudena and Sarah Smith (May 2020). *Baby Steps: The Gender Division of Childcare during the COVID-19 Pandemic*. 13302. Institute of Labor Economics (IZA). URL: <https://ideas.repec.org/p/iza/izadps/dp13302.html> (visited on 08/31/2020).
- Ten Hoeve, Youri, Jildou Talman, Jorrit van Mierlo, and Mirjam Engelen (Jan. 2021). “Evaluatie Wet Flexibel Werken”. Onderzoek in opdracht van het ministerie van Sociale Zaken en Werkgelegenheid. URL: <https://www.beleidsonderzoekers.nl/wp-content/uploads/2021/02/P0166-evaluatie-wet-flexibel-werken.pdf>.
- Van Soest, Arthur, Jim Been, Pia Pinger, Hans-Martin von Gaudecker, and Centerdata (Nov. 2019). *LISS Panel - Time Use and Consumption - Part 6*. DANS/KNAW. DOI: 10.17026/DANS-Z66-K49H. URL: <https://doi.org/10.17026/dans-z66-k49h>.
- Von Gaudecker, Hans-Martin and Centerdata (Apr. 2020a). *LISS Panel - Time Use and Consumption - Part 7 (Additional Coronavirus Part)*. DANS/KNAW. DOI: 10.17026/DANS-ZGP-MDKM. URL: <https://doi.org/10.17026/dans-zgp-mdkm> (visited on 12/14/2022).
- (Nov. 2020b). *LISS Panel - Time Use and Consumption - Part 8*. DANS/KNAW. DOI: 10.17026/DANS-ZZ9-9EDB. URL: <https://doi.org/10.17026/dans-zz9-9edb>.
- Von Gaudecker, Hans-Martin, Christian Zimpelmann, et al. (2021). *CoVID-19 Impact Lab Questionnaire Documentation*. DOI: 10.5281/zenodo.4338731. URL: <https://doi.org/10.5281/zenodo.4338730> (visited on 03/01/2021).
- Wiswall, Matthew and Basit Zafar (Feb. 1, 2018). “Preference for the Workplace, Investment in Human Capital, and Gender”. In: *The Quarterly Journal of Economics* 133.1, pp. 457–507. ISSN: 0033-5533. DOI: 10.1093/qje/qjx035. URL: <https://doi.org/10.1093/qje/qjx035> (visited on 10/13/2022).
- Zamarro, Gema and María J. Prados (Mar. 1, 2021). “Gender Differences in Couples’ Division of Childcare, Work and Mental Health during COVID-19”. In: *Review of Economics of the*

Household 19.1, pp. 11–40. ISSN: 1573-7152. DOI: 10.1007/s11150-020-09534-7. URL: <https://doi.org/10.1007/s11150-020-09534-7> (visited on 10/13/2022).

Zimpelmann, Christian, Hans-Martin von Gaudecker, Radost Holler, Lena Janys, and Bettina Siflinger (Dec. 2021). “Hours and Income Dynamics during the Covid-19 Pandemic: The Case of the Netherlands”. In: *Labour Economics* 73, p. 102055. ISSN: 09275371. DOI: 10.1016/j.labeco.2021.102055. URL: <https://linkinghub.elsevier.com/retrieve/pii/S0927537121000907> (visited on 03/14/2022).

Appendix A Details on datasets and data

A.1 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.¹¹

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.5a 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 remote work share in the NEA exhibits a similar distribution like the share of tasks that can

¹¹The 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-->.

be done from home variable in the LISS Sample (see Figure 4a). The distribution is bi-modal and men have, on average, a higher remote work share than women.

To be able to impute the remote work capability for each individual in the administrative records, we have to find highly predictive characteristics along which we can make the imputation. Table A.1 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.

We only consider the remote work share in the year 2020, since before this year there were no large differences in the remote work share across sectors and remote work shares were generally on a low level. Figures A.1, A.3, and A.4 illustrate this by showing the mean remote work share by sector for the years 2018, 2019 and 2020.

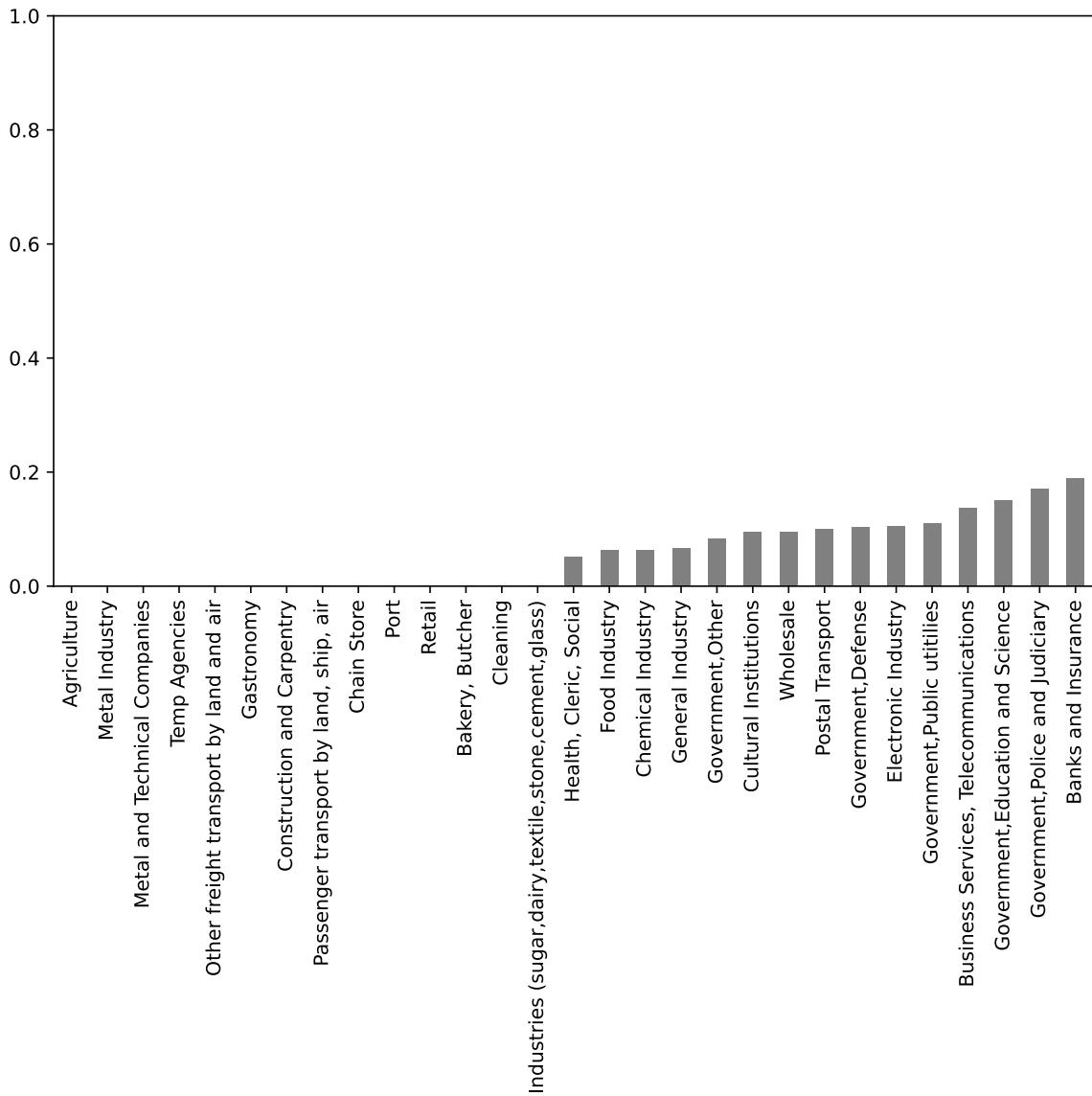
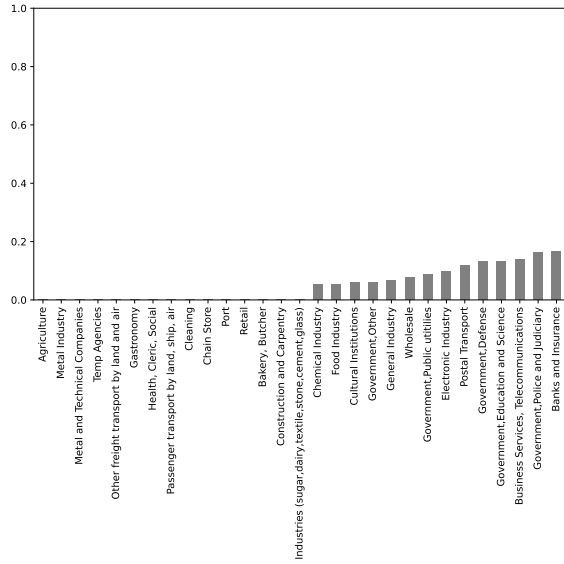
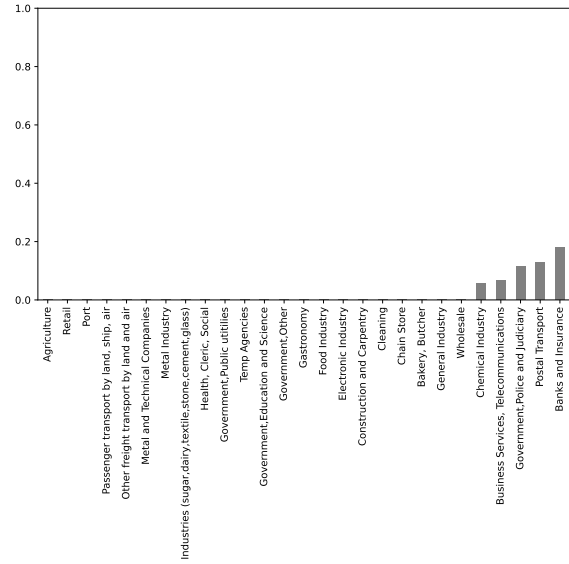


Figure A.1: Share of Remote Work by Sector 2018

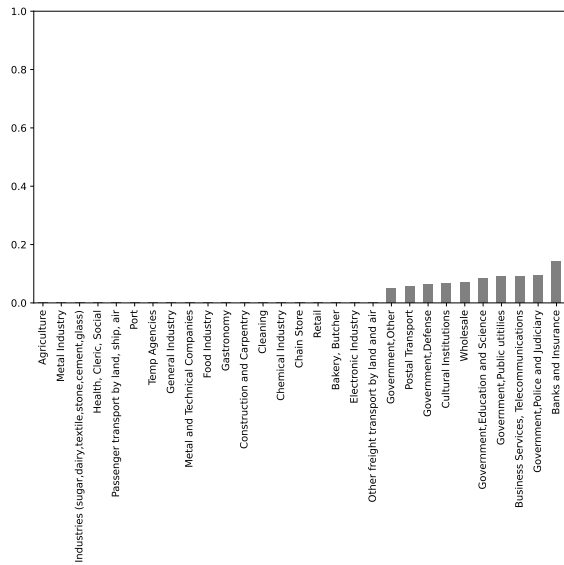
Notes: This figure displays the mean remote work share in the year 2018 aggregated by sector. The population are the participants of the National Working Conditions Survey (NEA) in the year 2018. The figure shows that the remote work potential does not vary substantially between sectors and is generally at a low level.



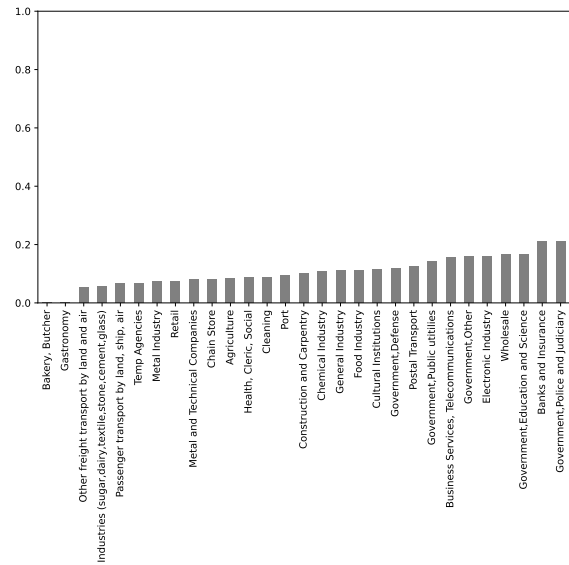
(a) Unknown Education



(b) Low Education



(c) Middle Education



(d) High Education

Figure A.2: Share of Remote Work by Sector and Education 2018

Notes:

Table A.1: Determinants remote work share in Fall 2020

	Share remote hours
Constant	0.44*** (0.0086)
Education: Low	-0.29*** (0.0079)
Education: Middle	-0.19*** (0.0046)
Education: Unknown	-0.16*** (0.0043)
Male	-0.0044 (0.0038)
Agriculture	-0.15*** (0.018)
Bakery, Butcher	-0.21*** (0.024)
Banks and Insurance	0.41*** (0.014)
Business Services	0.23*** (0.0088)
Chain Store	-0.16*** (0.015)
Chemical Industry	-0.029 (0.019)
Cleaning	-0.21*** (0.019)
Construction and Carpentry	-0.1*** (0.013)
Cultural Institutions	-0.0071 (0.023)
Electronic Industry	0.18*** (0.021)
Food Industry	-0.014 (0.02)
Gastronomy	-0.22*** (0.016)
General Industry	-0.019 (0.015)
Government, Defense	0.028 (0.023)
Government, Education	-0.14*** (0.0087)
Government, Other	0.099*** (0.014)
Government, Police	0.24*** (0.013)
Government, Public utilities	0.27*** (0.012)
Health, Cleric, Social	-0.15*** (0.0089)
Industries (sugar, dairy, textile, stone, cement, glass)	-0.076*** (0.021)
Metal Industry	-0.03** (0.014)
Metal and technical companies	-0.15*** (0.011)
Other freight transport	-0.16*** (0.015)
Passenger transport	-0.093*** (0.016)
Port	0.022 (0.021)
Postal Transport	-0.23*** (0.029)
Retail	-0.17*** (0.013)
Temp Agencies	-0.068*** (0.014)
Wholesale	0.016 (0.01)
N children	-0.0043*** (0.0016)
Observations	37295
R ²	0.27

Notes: The table displays the regression results from regressing the remote work share in 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.

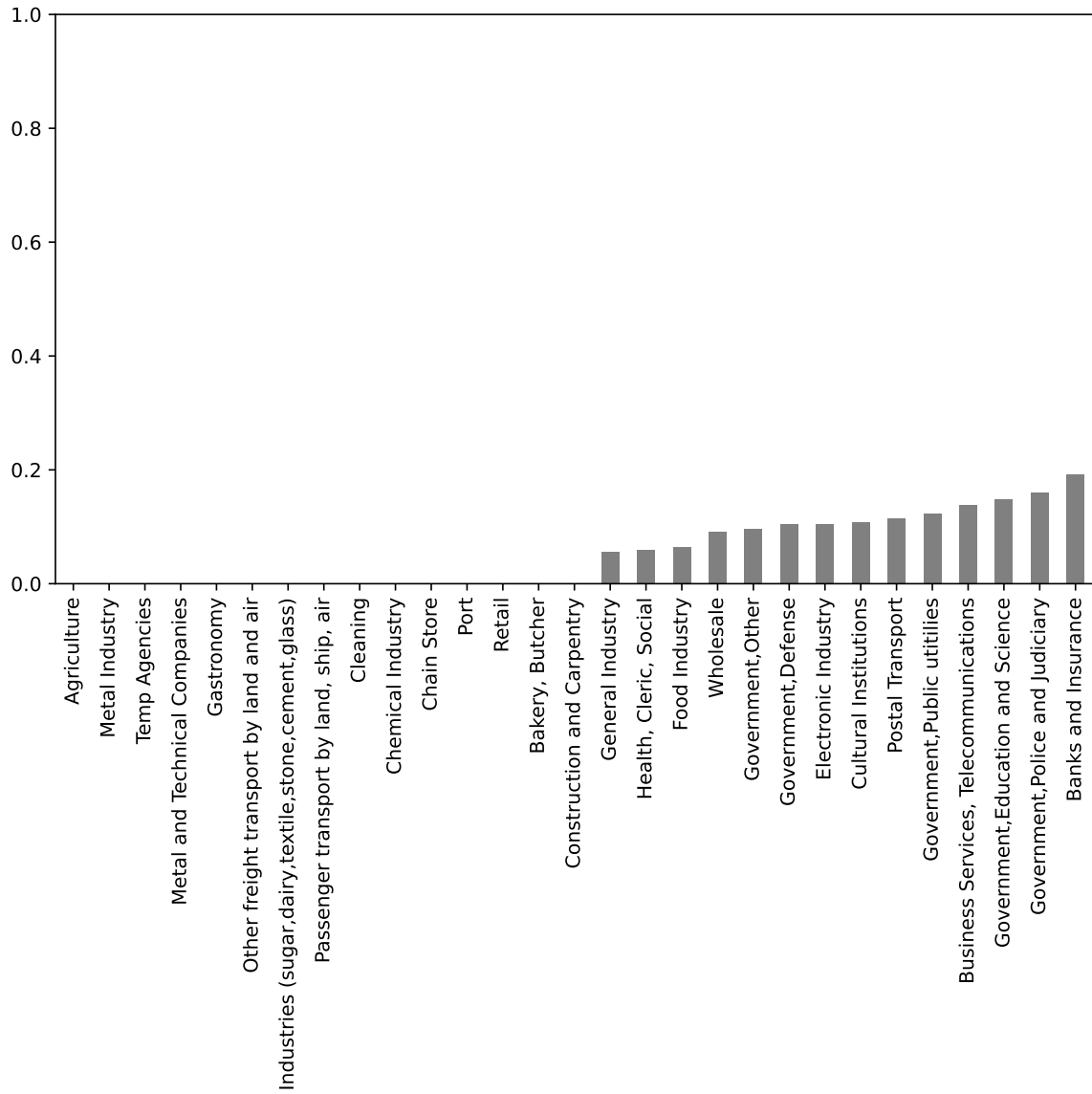


Figure A.3: Share of Remote Work by Sector 2019

Notes: This figure displays the mean remote work share in the year 2019 aggregated by sector. The population are the participants of the National Working Conditions Survey (NEA) in the year 2019. The figure shows that the remote work potential does not vary substantially between sectors and is generally at a low level.

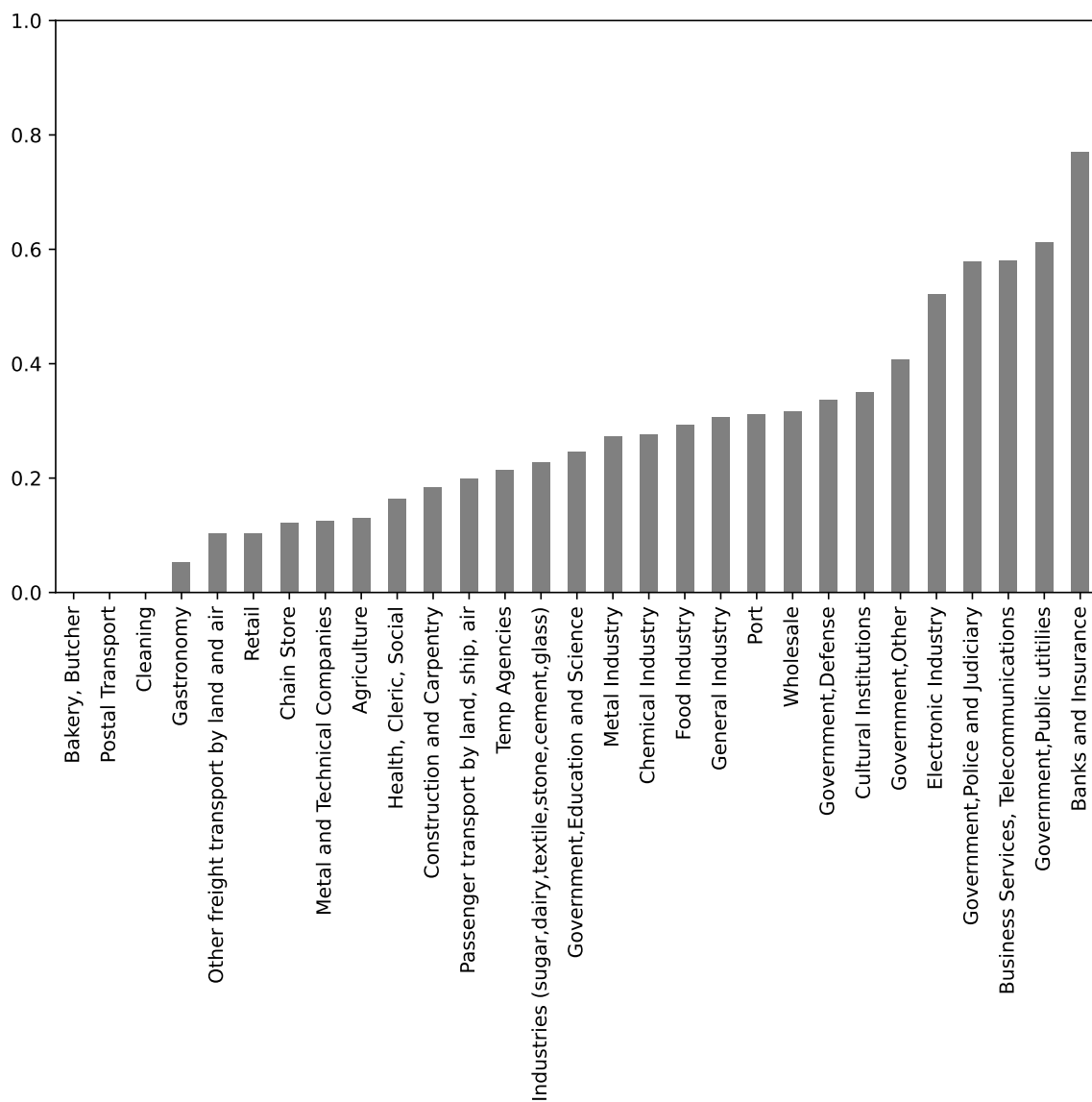


Figure A.4: Share of Remote Work by Sector 2020

Notes: This figure displays the mean remote work share in the year 2020 aggregated by sector. The population are the participants of the National Working Conditions Survey (NEA) in the year 2020. The figure shows that the remote work potential varies substantially between sectors.

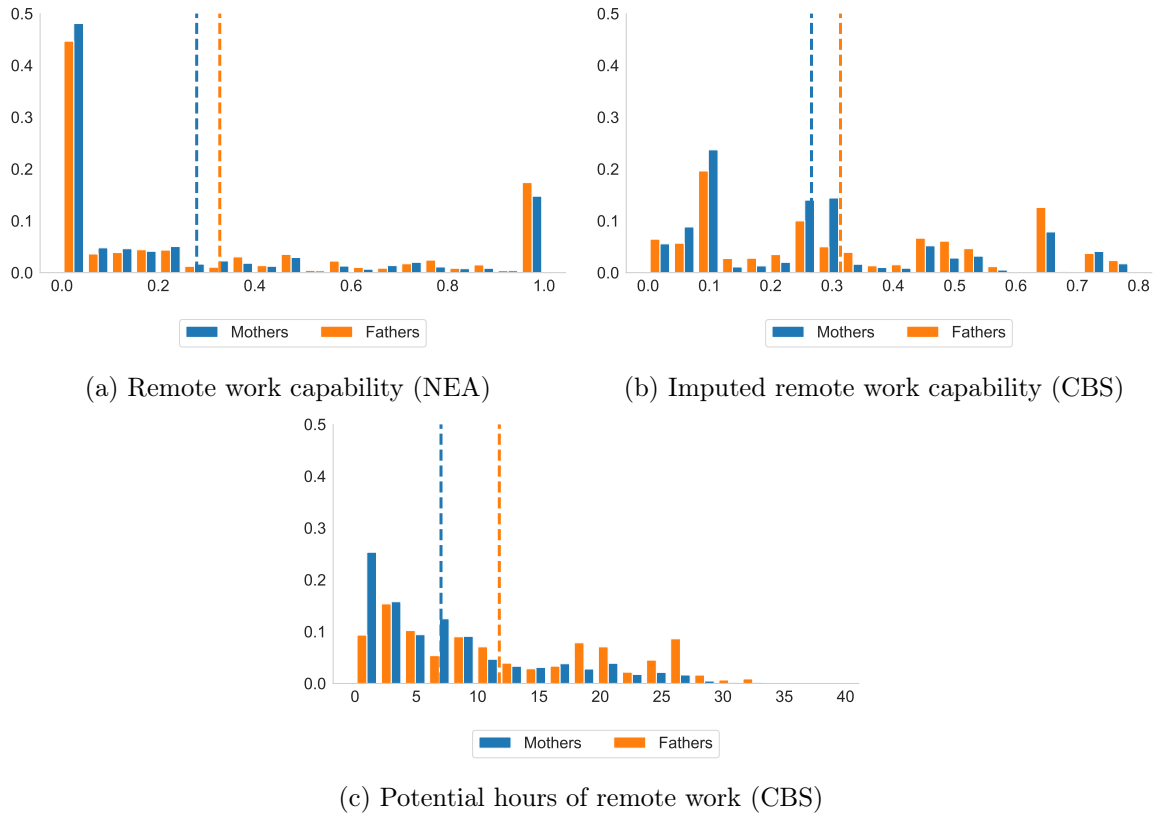


Figure A.5: Potential remote work by gender: in NEA and CBS

Notes: Figure A.5a 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. Figure A.5b shows the distribution of the imputed remote work capability by gender in the CBS. Dashed vertical lines indicate the mean for each gender. 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 these two variables. The figure shows that after the imputation, the distribution naturally looks less bi-modal, since averaging across sector and education reduces the occurrence of extreme values of the remote work capability. Figure ?? shows the distribution of the potential hours of remote work by gender in the CBS. Dashed vertical lines indicate the mean for each gender. 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 pre-covid (November 2019) working hours to obtain the potential hours of remote work.

A.2 Additional descriptive statistics

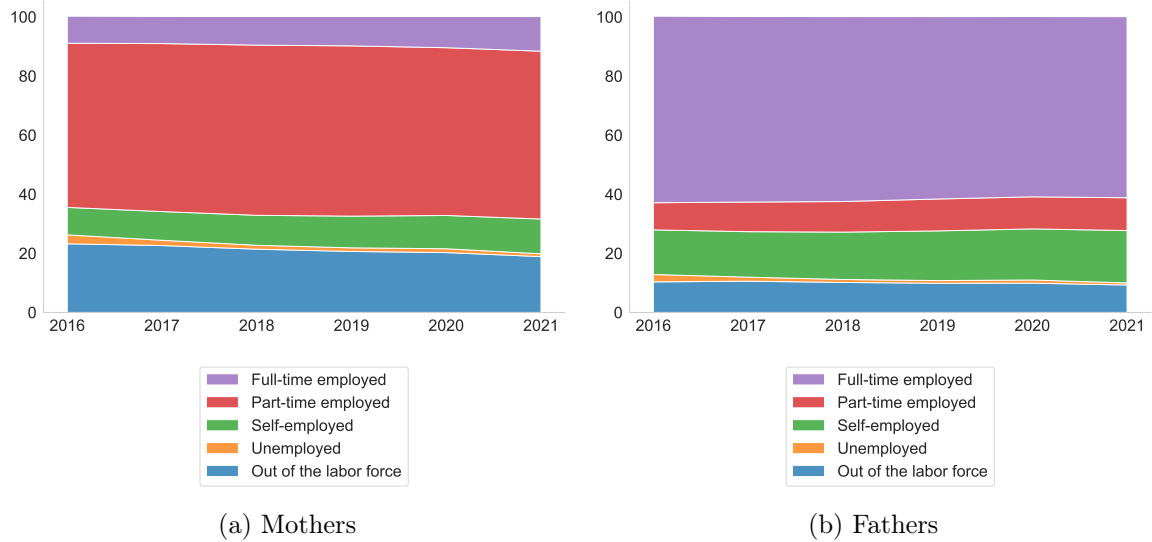


Figure A.6: Labor force participation and hours categories over time

Notes: The figure provides an illustration of in Table 2. The data source is a 20 % sample of 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.2: 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 (0.38)	7.17 (0.28)	2.05 (0.05)	0.45 (0.03)	0.26 (0.03)	0.03 (0.01)	0.26 (0.03)	260
	2020-04	40.90 (0.37)	7.18 (0.29)	2.05 (0.05)	0.45 (0.03)	0.25 (0.03)	0.05 (0.01)	0.25 (0.03)	280
	2020-11	40.09 (0.35)	6.85 (0.26)	2.03 (0.04)	0.44 (0.03)	0.26 (0.02)	0.04 (0.01)	0.26 (0.02)	339
	2021-11	39.68 (0.38)	6.29 (0.27)	2.01 (0.05)	0.54 (0.03)	0.30 (0.03)	0.02 (0.01)	0.14 (0.02)	311
	Fathers	2019-11	42.63 (0.41)	6.94 (0.30)	2.10 (0.05)	0.48 (0.03)	0.25 (0.03)	0.03 (0.01)	0.24 (0.03)
	2020-04	42.96 (0.41)	6.80 (0.30)	2.07 (0.05)	0.42 (0.03)	0.27 (0.03)	0.05 (0.01)	0.25 (0.03)	257
	2020-11	42.33 (0.39)	6.69 (0.28)	2.07 (0.05)	0.43 (0.03)	0.25 (0.03)	0.05 (0.01)	0.27 (0.03)	283
	2021-11	42.35 (0.40)	6.60 (0.29)	2.08 (0.05)	0.51 (0.03)	0.27 (0.03)	0.04 (0.01)	0.18 (0.02)	275

(b) CBS

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

Notes: Table A.2a 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.2a displays means and standard errors of basic demographic characteristics of the 20 % sample 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.3: 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 (6.61)	39.0 (6.72)	41.47 (6.84)	41.41 (6.99)
Age youngest child	6.76 (4.84)	6.7 (4.86)	6.76 (4.84)	6.66 (4.83)
Education: High	0.38 (0.48)	0.44 (0.5)	0.35 (0.48)	0.39 (0.49)
Education: Low	0.08 (0.27)	0.07 (0.25)	0.08 (0.28)	0.08 (0.27)
Education: Middle	0.28 (0.45)	0.31 (0.46)	0.25 (0.43)	0.29 (0.45)
Education: Unknown	0.27 (0.44)	0.18 (0.39)	0.32 (0.46)	0.24 (0.42)
Full-time	0.11 (0.32)	0.14 (0.35)	0.83 (0.38)	0.83 (0.38)
Number of children	1.96 (0.77)	1.94 (0.78)	1.98 (0.8)	1.96 (0.8)
Out of labor force	0.05 (0.23)	0.04 (0.2)	0.03 (0.17)	0.02 (0.15)
Part-time	0.83 (0.38)	0.81 (0.4)	0.14 (0.34)	0.14 (0.35)
Potential commuting gains	6.02 (12.36)	6.11 (11.93)	9.94 (16.04)	10.15 (16.13)
Potential hours remote work	7.01 (6.87)	7.75 (7.13)	11.77 (8.72)	12.37 (8.89)
Remote work capability (imputed)	26.65 (21.73)	27.56 (21.52)	31.38 (22.93)	32.35 (23.02)
Unemployed	0.01 (0.09)	0.01 (0.11)	0.01 (0.08)	0.01 (0.1)
Working hours	24.55 (8.37)	26.4 (7.99)	38.33 (5.78)	38.59 (5.6)
Working hours (unconditional)	23.09 (9.95)	25.08 (9.69)	37.01 (8.97)	37.52 (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.4: 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 (0.024)	0.008 (0.005)	0.131 (0.021)	0.581 (0.031)	0.092 (0.018)
	2020-04	0.146 (0.021)	0.004 (0.004)	0.132 (0.020)	0.593 (0.029)	0.125 (0.020)
	2020-11	0.156 (0.020)	0.003 (0.003)	0.103 (0.017)	0.605 (0.027)	0.133 (0.018)
	2021-11	0.138 (0.020)	0.006 (0.005)	0.122 (0.019)	0.621 (0.028)	0.113 (0.018)
	Fathers	2019-11	0.026 (0.011)	0 (0)	0.074 (0.017)	0.170 (0.025)
	2020-04	0.016 (0.008)	0.004 (0.004)	0.066 (0.016)	0.171 (0.024)	0.743 (0.027)
	2020-11	0.025 (0.009)	0.004 (0.004)	0.074 (0.016)	0.152 (0.021)	0.746 (0.026)
	2021-11	0.018 (0.008)	0.004 (0.004)	0.076 (0.016)	0.164 (0.022)	0.738 (0.027)

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.5: Total working hours over time

	CBS			LISS		
	All	Fathers	Mothers	All	Fathers	Mothers
2016-11	32.3 (0.0162)	38.6 (0.0134)	25.3 (0.0204)			
2017-11	32.3 (0.016)	38.5 (0.0135)	25.5 (0.0202)			
2018-11	32.4 (0.0158)	38.5 (0.0136)	25.9 (0.0199)			
2019-11	32.4 (0.0156)	38.4 (0.0136)	26.1 (0.0198)	28.7 (0.607)	37.3 (0.577)	21 (0.775)
2020-04				28.8 (0.58)	36.6 (0.572)	21.6 (0.764)
2020-11	32.5 (0.0154)	38.3 (0.0134)	26.5 (0.0198)	29.1 (0.539)	36.9 (0.536)	22.5 (0.711)
2021-11	32.8 (0.0151)	38.3 (0.0133)	27 (0.0195)	29.6 (0.541)	37.6 (0.499)	22.6 (0.716)

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 for a 20 % sample 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.6: Remote work dummy over time

	LISS		
	All	Fathers	Mothers
2020-02	0.32 (0.02)	0.36 (0.031)	0.28 (0.027)
2020-04	0.58 (0.021)	0.63 (0.03)	0.54 (0.03)
2020-11	0.48 (0.02)	0.56 (0.029)	0.42 (0.027)
2021-11	0.49 (0.02)	0.56 (0.03)	0.42 (0.028)

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.7: Remote work share over time

	LISS		
	All	Fathers	Mothers
2020-02	0.12 (0.012)	0.12 (0.015)	0.13 (0.018)
2020-04	0.47 (0.022)	0.49 (0.031)	0.44 (0.031)
2020-11	0.37 (0.021)	0.43 (0.029)	0.33 (0.03)
2021-11	0.34 (0.021)	0.35 (0.026)	0.33 (0.031)

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.8: Remote working hours over time

	LISS		
	All	Fathers	Mothers
2020-02	4.1 (0.4)	4.7 (0.63)	3.5 (0.51)
2020-04	15 (0.74)	18 (1.2)	12 (0.88)
2020-11	12 (0.68)	16 (1.1)	9.4 (0.79)
2021-11	11 (0.63)	14 (1)	8.8 (0.76)

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: Commuting hours over time

	LISS		
	All	Fathers	Mothers
2019-11	4.1 (0.2)	5.8 (0.33)	2.6 (0.18)
2020-04	1.9 (0.19)	2.4 (0.29)	1.5 (0.24)
2020-11	2.2 (0.12)	2.9 (0.2)	1.6 (0.14)
2021-11	2.8 (0.17)	3.6 (0.26)	2.1 (0.23)

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

Table A.10: Childcare hours over time

	LISS		
	All	Fathers	Mothers
2019-11	23.1 (0.854)	16.8 (0.926)	28.7 (1.3)
2020-04	35.1 (0.955)	29.6 (1.32)	40.3 (1.31)
2020-11	23.4 (0.776)	20.1 (1.07)	26.1 (1.09)
2021-11	24.6 (0.799)	19.3 (0.968)	29.3 (1.18)

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	5.15*** (1.16)	1.16 (0.76)	4.64*** (0.27)	4.05*** (0.37)
2020-04	11.81*** (0.87)	2.71*** (0.87)	-2.66*** (0.28)	-0.92* (0.49)
2020-11	9.54*** (0.82)	0.01 (0.72)	-2.26*** (0.22)	-0.82** (0.33)
2021-11	7.09*** (0.74)	0.43 (0.74)	-1.6*** (0.26)	-0.17 (0.46)
Pot. hours remote work		0.21*** (0.04)		0.04** (0.02)
Pot. hours remote work × 2020-04		0.61*** (0.06)		-0.11*** (0.02)
Pot. hours remote work × 2020-11		0.60*** (0.05)		-0.09*** (0.02)
Pot. hours remote work × 2021-11		0.41*** (0.05)		-0.09*** (0.02)
N children == 2	-0.06 (1.45)	-0.15 (0.84)	-0.32 (0.23)	-0.29 (0.22)
N children == 3	-2.03 (1.70)	-0.38 (1.00)	0.01 (0.34)	-0.07 (0.32)
N children == 4	-0.32 (2.52)	0.28 (1.82)	1.36 (0.94)	1.31 (0.89)
N children >4	-4.06 (2.68)	0.94 (0.88)	1.38 (1.08)	0.98 (0.95)
Age youngest child (std)	-0.75 (0.56)	0.48 (0.37)	0.21** (0.11)	0.13 (0.10)
Observations	1,876	1,876	1,876	1,876
R^2	0.078	0.462	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	0.93 (0.88)	6.14*** (0.67)
2020-04	3.64** (1.42)	-2.34*** (0.78)
2020-11	1.38 (1.26)	-1.71*** (0.64)
2021-11	0.67 (1.25)	-1.01 (0.76)
Pot. hours remote work	0.21*** (0.04)	0.00 (0.02)
Pot. hours remote work \times 2020-04	0.60*** (0.08)	-0.09*** (0.03)
Pot. hours remote work \times 2020-11	0.56*** (0.07)	-0.08*** (0.02)
Pot. hours remote work \times 2021-11	0.41*** (0.06)	-0.07*** (0.03)
Pot. hours remote work \times Female	0.02 (0.08)	0.04 (0.03)
Pot. hours remote work \times Female \times 2020-04	0.01 (0.11)	-0.02 (0.04)
Pot. hours remote work \times Female \times 2020-11	0.06 (0.11)	-0.0 (0.03)
Pot. hours remote work \times Female \times 2021-11	-0.02 (0.10)	-0.02 (0.04)
Youngest child age	0-15	0-15
Observations	1,876	1,876
R^2	0.165	0.463

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 interacted with gender. 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) 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)	(3)	(4)
Constant	28.22*** (1.43)	19.56*** (1.69)	27.34*** (2.72)	37.79*** (2.88)
2020-04	6.20*** (1.40)	6.69*** (2.14)	10.93*** (2.22)	0.38 (2.35)
2020-11	-4.78*** (1.30)	1.52 (1.80)	-3.84* (2.05)	-13.24*** (2.34)
2021-11	-3.19*** (1.21)	-0.51 (1.75)	0.06 (2.07)	-10.1*** (2.12)
Pot. hours remote work	-0.26*** (0.05)	-0.04 (0.05)	-0.13 (0.09)	-0.07 (0.49)
Pot. hours remote work × 2020-04	0.49*** (0.07)	0.46*** (0.09)	0.35** (0.14)	1.78*** (0.44)
Pot. hours remote work × 2020-11	0.38*** (0.07)	0.21** (0.08)	0.28** (0.13)	1.14* (0.62)
Pot. hours remote work × 2021-11	0.26*** (0.06)	0.19*** (0.07)	0.12 (0.13)	0.74 (0.52)
N children == 2	-0.82 (1.20)	-0.81 (1.65)	-1.68 (2.25)	0.80 (2.53)
N children == 3	-1.63 (1.45)	-1.7 (2.12)	-2.28 (2.70)	-2.25 (2.67)
N children == 4	-1.25 (2.59)	-1.08 (3.48)	-2.94 (7.34)	0.18 (4.55)
N children >4	3.46* (2.06)	3.24 (3.86)	0.60 (2.33)	1.11 (4.33)
Age youngest child (std)	-9.22*** (0.48)	-6.66*** (0.70)	-11.07*** (0.85)	-11.48*** (0.90)
Working hours (2019-11)	All	>34	20-34	<20
Observations	2,234	1,010	706	518
R^2	0.273	0.245	0.375	0.359

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 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. 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)	(3)	(4)
Constant	25.84*** (1.46)	20.42*** (1.83)	25.58*** (2.53)	30.17*** (3.03)
2020-04	5.04*** (1.62)	3.11 (2.27)	10.47*** (2.41)	-0.6 (3.53)
2020-11	-6.56*** (1.37)	-3.3* (1.75)	-4.47** (2.17)	-15.31*** (3.41)
2021-11	-5.45*** (1.34)	-4.94*** (1.68)	-0.9 (2.30)	-13.17*** (2.92)
Pot. hours remote work	-0.19*** (0.05)	-0.07 (0.05)	-0.02 (0.10)	0.18 (0.44)
Pot. hours remote work × 2020-04	0.54*** (0.07)	0.58*** (0.09)	0.36*** (0.14)	1.89*** (0.46)
Pot. hours remote work × 2020-11	0.47*** (0.07)	0.40*** (0.08)	0.29** (0.13)	0.88 (0.60)
Pot. hours remote work × 2021-11	0.38*** (0.06)	0.37*** (0.07)	0.18 (0.13)	0.96* (0.50)
N children == 2	-0.59 (1.23)	-0.96 (1.61)	-1.55 (2.25)	6.71*** (2.57)
N children == 3	-0.53 (1.52)	-1.57 (2.03)	-1.54 (2.64)	4.51 (3.08)
N children == 4	-0.87 (3.00)	-0.37 (3.43)	-4.57 (6.96)	10.36 (6.39)
N children >4	5.84*** (2.14)	2.76 (3.70)	2.69 (2.12)	10.11*** (2.34)
Age youngest child (std)	-8.54*** (0.53)	-6.5*** (0.70)	-10.57*** (0.90)	-11.65*** (1.33)
Working hours (2019-11)	All	>34	20-34	<20
Observations	1,876	979	681	216
R^2	0.293	0.282	0.38	0.483

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 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). 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	18.09*** (1.17)	18.84*** (1.23)	17.88*** (1.41)
2020-04	12.43*** (1.46)	10.33*** (1.42)	10.36*** (1.43)
2020-11	2.90** (1.28)	1.20 (1.29)	1.72 (1.27)
2021-11	1.70 (1.13)	0.39 (1.15)	0.53 (1.18)
Mother	12.46*** (1.31)	11.11*** (1.34)	12.51*** (2.09)
Mother × 2020-04	-0.43 (1.94)	3.16 (1.92)	3.05 (1.93)
Mother × 2020-11	-6.01*** (1.84)	-3.24* (1.86)	-3.33* (1.85)
Mother × 2021-11	-3.4** (1.63)	-1.41 (1.66)	-1.38 (1.65)
Pot. hours remote work (std)		-2.34*** (0.68)	-1.49** (0.73)
Pot. hours remote work (std) × 2020-04		7.27*** (1.04)	7.56*** (1.31)
Pot. hours remote work (std) × 2020-11		5.06*** (1.01)	3.57*** (1.18)
Pot. hours remote work (std) × 2021-11		3.56*** (0.88)	3.16*** (0.99)
Pot. hours remote work (std) × Mother × 2020-04			-0.66 (2.02)
Pot. hours remote work (std) × Mother × 2020-11			3.73** (1.86)
Pot. hours remote work (std) × Mother × 2021-11			1.04 (1.89)
N children == 2	-0.33 (1.17)	-0.29 (1.15)	0.48 (1.52)
N children == 3	-1.04 (1.41)	-0.81 (1.38)	0.05 (1.93)
N children == 4	-0.3 (2.64)	0.13 (2.60)	1.12 (3.69)
N children >4	1.15 (2.48)	2.00 (2.39)	6.67* (3.87)
Age youngest child (std)	-6.6*** (0.63)	-6.4*** (0.63)	-6.4*** (0.64)
Age youngest child (std) × Mother	58 -5.25*** (0.81)	-5.16*** (0.81)	-5.19*** (0.85)
Observations	2,234	2,234	2,234
R ²	0.326	0.347	0.349

Notes: *** $p < 0.01$ ** $p < 0.05$ * $p < 0.1$. Standard errors obtained by clustering on the household level All

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	16.97*** (1.19)	17.13*** (1.16)	16.58*** (1.33)
2020-04	13.07*** (1.47)	12.3*** (1.39)	12.37*** (1.38)
2020-11	3.66*** (1.29)	2.43** (1.24)	2.80** (1.20)
2021-11	2.04* (1.12)	1.05 (1.08)	1.29 (1.06)
Mother	11.15*** (1.33)	10.39*** (1.37)	11.09*** (2.17)
Mother × 2020-04	1.20 (2.06)	3.95** (1.97)	3.90* (2.01)
Mother × 2020-11	-5.49*** (1.95)	-2.65 (1.91)	-2.35 (1.92)
Mother × 2021-11	-2.94* (1.74)	-0.76 (1.74)	-0.62 (1.76)
Pot. hours remote work (std)		-1.75** (0.70)	-1.02 (0.70)
Pot. hours remote work (std) × 2020-04		8.24*** (1.12)	8.14*** (1.33)
Pot. hours remote work (std) × 2020-11		6.79*** (1.04)	4.80*** (1.18)
Pot. hours remote work (std) × 2021-11		5.49*** (0.97)	4.17*** (1.02)
Pot. hours remote work (std) × Mother			-1.87 (1.38)
Pot. hours remote work (std) × Mother × 2020-04			0.28 (2.13)
Pot. hours remote work (std) × Mother × 2020-11			4.96** (1.96)
Pot. hours remote work (std) × Mother × 2021-11			3.21 (1.99)
Observations	1,876	1,876	1,876
R^2	0.319	0.368	0.37

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. 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

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

B.4 Labor supply

Table B.7: Event study: Women with children 0-15

	Working hours		
	(1)	(2)	(3)
Constant	16.86*** (0.07)	18.87*** (0.06)	20.4*** (0.06)
Partner: Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic	0.01*** (0.00)	0.00 (0.00)	-0.0* (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			-0.0 (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			0.00 (0.00)

Partner: Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			0.00 (0.00)
Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic		0.03*** (0.00)	0.02*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic		0.01*** (0.00)	0.01*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic		0.02*** (0.00)	0.02*** (0.00)
Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			0.02*** (0.00)
Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			0.01*** (0.00)
Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			0.02*** (0.00)
Time rel. treat. == -1	0.23*** (0.02)	-0.04* (0.02)	-0.87*** (0.02)
Time rel. treat. == 1	-0.14*** (0.02)	0.25*** (0.02)	0.00 (0.02)
Time rel. treat. == 2	0.07*** (0.02)	0.79*** (0.02)	0.45*** (0.02)
Pandemic	2.38*** (0.02)	2.45*** (0.03)	1.47*** (0.02)
Time rel. treat. == -1 \times Pandemic	-0.68*** (0.03)	-0.83*** (0.03)	-0.0 (0.03)
Time rel. treat. == 1 \times Pandemic	-0.53*** (0.03)	-0.59*** (0.03)	-0.32*** (0.03)
Time rel. treat. == 2 \times Pandemic	-0.43*** (0.03)	-0.52*** (0.03)	-0.15*** (0.03)
Pot. hrs remote work		0.66*** (0.00)	0.76*** (0.00)
Pot. hrs remote work \times Pandemic		-0.07*** (0.00)	-0.07*** (0.00)
Pot. hrs remote work \times Time rel. treat. == -1		0.02*** (0.00)	0.03*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 1		-0.04*** (0.00)	-0.06*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 2		-0.08*** (0.00)	-0.1*** (0.00)
Partner: Pot. hrs remote work	0.07*** (0.00)	-0.05*** (0.00)	-0.04*** (0.00)
Partner: Pot. hrs remote work \times Pandemic	-0.01*** (0.00)	-0.0 (0.00)	0.00 (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == -1	0.00	-0.0	0.00***

	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 1	0.00*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 2	0.00*** (0.00)	0.02*** (0.00)	0.01*** (0.00)
Partner: Pot. commuting gains			-0.06*** (0.00)
Partner: Pot. commuting gains \times Pandemic			0.00** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == -1			-0.0 (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 1			0.01*** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 2			0.02*** (0.00)
Pot. commuting gains			-0.06*** (0.00)
Pot. commuting gains \times Pandemic			-0.0** (0.00)
Pot. commuting gains \times Time rel. treat. == -1			-0.02*** (0.00)
Pot. commuting gains \times Time rel. treat. == 1			0.00*** (0.00)
Pot. commuting gains \times Time rel. treat. == 2			0.00*** (0.00)
N children == 2	-1.58*** (0.02)	-1.17*** (0.01)	-1.2*** (0.01)
N children == 3	-3.32*** (0.02)	-2.19*** (0.02)	-2.17*** (0.02)
N children == 4	-5.82*** (0.06)	-3.64*** (0.05)	-3.55*** (0.05)
N children >4	-8.89*** (0.15)	-5.63*** (0.13)	-5.51*** (0.13)
Age	0.18*** (0.00)	0.00** (0.00)	-0.01** (0.00)
Partner: Age	0.04*** (0.00)	0.02*** (0.00)	0.02*** (0.00)
Youngest child age	0-15	0-15	0-15
Observations	5,160,628	5,160,628	4,934,264
R^2	0.041	0.216	0.233

Notes: The table displays the coefficients of the event-study DiD pooled for mothers with a youngest child below 16. The first column includes only the partner remote work capability. The second column includes both the own and the partner remote work capability. The third column includes both the own and the partner remote work capability and the own and partner potential commuting gains. Remote work capability is 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 share 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. The exact procedure of the variable generation and pooling is described in Section 4.2. 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.

Table B.8: Event study: Women with children 0-5

	Working hours		
	(1)	(2)	(3)
Constant	13.65*** (0.09)	16.76*** (0.08)	18.68*** (0.07)
Partner: Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic	0.01** (0.00)	-0.0 (0.00)	-0.01** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic	0.01*** (0.00)	0.01*** (0.00)	0.01*** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			-0.0 (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			0.00 (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			0.00 (0.00)
Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic		0.03*** (0.00)	0.02*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic		0.01*** (0.00)	0.01 (0.00)
Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic		0.02*** (0.00)	0.00 (0.00)
Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			0.02*** (0.00)
Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			0.01*** (0.00)
Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			0.02*** (0.00)
Time rel. treat. == -1	0.48*** (0.03)	0.24*** (0.03)	-0.85*** (0.03)
Time rel. treat. == 1	-0.36*** (0.03)	0.01 (0.03)	-0.37*** (0.03)
Time rel. treat. == 2	-0.32*** (0.03)	0.32*** (0.03)	-0.21*** (0.03)
Pandemic	1.89*** (0.04)	2.03*** (0.04)	0.72*** (0.04)
Time rel. treat. == -1 \times Pandemic	-0.73*** (0.04)	-0.88*** (0.05)	0.21*** (0.04)
Time rel. treat. == 1 \times Pandemic	-0.52*** (0.04)	-0.58*** (0.04)	-0.17*** (0.04)
Time rel. treat. == 2 \times Pandemic	-0.38*** (0.04)	-0.47*** (0.04)	0.07* (0.04)

	(0.04)	(0.05)	(0.04)
Pot. hrs remote work		0.62***	0.69***
		(0.00)	(0.00)
Pot. hrs remote work × Pandemic		-0.05***	-0.04***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == -1		0.02***	0.04***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == 1		-0.04***	-0.06***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == 2		-0.06***	-0.08***
		(0.00)	(0.00)
Partner: Pot. hrs remote work	0.08***	-0.04***	-0.04***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Pandemic	-0.01***	-0.0	0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == -1	0.00	0.00	0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == 1	0.00	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == 2	-0.0	0.01***	0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. commuting gains			-0.05***
			(0.00)
Partner: Pot. commuting gains × Pandemic			0.00
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == -1			-0.0
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == 1			0.01***
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == 2			0.01***
			(0.00)
Pot. commuting gains			-0.06***
			(0.00)
Pot. commuting gains × Pandemic			-0.01***
			(0.00)
Pot. commuting gains × Time rel. treat. == -1			-0.02***
			(0.00)
Pot. commuting gains × Time rel. treat. == 1			0.00
			(0.00)
Pot. commuting gains × Time rel. treat. == 2			0.00
			(0.00)
N children == 2	-1.98***	-1.42***	-1.45***
	(0.02)	(0.02)	(0.02)

N children == 3	-4.43*** (0.03)	-3.07*** (0.03)	-3.02*** (0.03)
N children == 4	-7.6*** (0.07)	-5.05*** (0.06)	-4.9*** (0.06)
N children >4	-10.97*** (0.18)	-7.33*** (0.16)	-7.17*** (0.17)
Age	0.31*** (0.00)	0.11*** (0.00)	0.09*** (0.00)
Partner: Age	0.02*** (0.00)	0.00** (0.00)	0.01*** (0.00)
Youngest child age	0-15	0-15	0-15
Observations	2,653,084	2,653,084	2,524,400
R^2	0.058	0.215	0.231

Notes: The table displays the coefficients of the event-study DiD pooled for mothers with a youngest child below 6. The first column includes only the partner remote work capability. The second column includes both the own and the partner remote work capability. The third column includes both the own and the partner remote work capability and the own and partner potential commuting gains. Remote work capability is 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 share 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. The exact procedure of the variable generation and pooling is described in Section 4.2. 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.

Table B.9: Event study: Men with children 0-15

	Working hours		
	(1)	(2)	(3)
Constant	38.97*** (0.05)	38.59*** (0.06)	39.75*** (0.05)
Partner: Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic	0.00* (0.00)	0.00 (0.00)	0.01*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic	0.02*** (0.00)	0.01** (0.00)	0.01*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic	0.02*** (0.00)	0.01*** (0.00)	0.02*** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			-0.0* (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			-0.0** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			-0.0 (0.00)
Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic		0.01*** (0.00)	-0.02*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic		0.03*** (0.00)	0.02*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic		0.04*** (0.00)	0.02*** (0.00)
Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			0.01*** (0.00)
Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			0.00** (0.00)
Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			0.00*** (0.00)
Time rel. treat. == -1	0.69*** (0.02)	0.67*** (0.02)	-0.2*** (0.02)
Time rel. treat. == 1	0.60*** (0.02)	0.90*** (0.02)	0.48*** (0.02)
Time rel. treat. == 2	1.36*** (0.02)	1.83*** (0.03)	1.29*** (0.02)
Pandemic	1.52*** (0.02)	1.82*** (0.03)	0.70*** (0.02)
Time rel. treat. == -1 \times Pandemic	-0.54*** (0.02)	-0.59*** (0.03)	0.26*** (0.03)
Time rel. treat. == 1 \times Pandemic	-1.05*** (0.02)	-1.35*** (0.03)	-0.93*** (0.03)
Time rel. treat. == 2 \times Pandemic	-1.56*** (0.02)	-1.9*** (0.03)	-1.34*** (0.03)

	(0.02)	(0.03)	(0.03)
Pot. hrs remote work		0.12***	0.12***
		(0.00)	(0.00)
Pot. hrs remote work × Pandemic		-0.03***	-0.0***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == -1		-0.0	0.02***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == 1		-0.03***	-0.03***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == 2		-0.04***	-0.04***
		(0.00)	(0.00)
Partner: Pot. hrs remote work	-0.07***	-0.11***	-0.1***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Pandemic	-0.01***	-0.0*	-0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == -1	-0.01***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == 1	-0.01***	0.00	-0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == 2	-0.01***	0.00	-0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. commuting gains			-0.02***
			(0.00)
Partner: Pot. commuting gains × Pandemic			-0.0***
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == -1			0.00
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == 1			0.01***
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == 2			0.01***
			(0.00)
Pot. commuting gains			-0.02***
			(0.00)
Pot. commuting gains × Pandemic			-0.0
			(0.00)
Pot. commuting gains × Time rel. treat. == -1			-0.01***
			(0.00)
Pot. commuting gains × Time rel. treat. == 1			0.00***
			(0.00)
Pot. commuting gains × Time rel. treat. == 2			0.01***
			(0.00)
N children == 2	0.34***	0.27***	0.21***
	(0.01)	(0.01)	(0.01)

N children == 3	0.27*** (0.02)	0.16*** (0.02)	0.13*** (0.02)
N children == 4	0.08* (0.04)	0.06 (0.04)	0.11*** (0.04)
N children >4	0.17 (0.12)	0.29** (0.11)	0.32*** (0.11)
Age	-0.07*** (0.00)	-0.06*** (0.00)	-0.06*** (0.00)
Partner: Age	-0.01*** (0.00)	-0.03*** (0.00)	-0.04*** (0.00)
Youngest child age	0-15	0-15	0-15
Observations	5,070,314	5,070,314	4,854,396
R^2	0.013	0.022	0.023

Notes: The table displays the coefficients of the event-study DiD pooled for fathers with a youngest child below 16. The first column includes only the partner remote work capability. The second column includes both the own and the partner remote work capability. The third column includes both the own and the partner remote work capability and the own and partner potential commuting gains. Remote work capability is 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 share 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. The exact procedure of the variable generation and pooling is described in Section 4.2. 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.

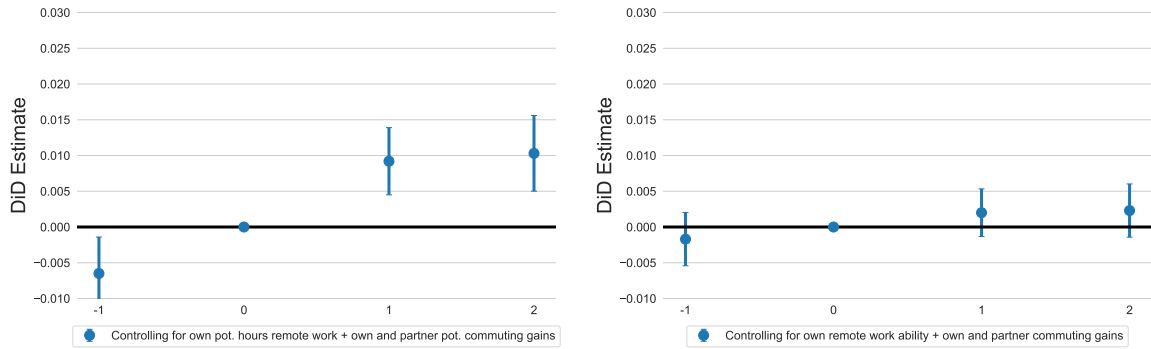
Table B.10: Event study: Men with children 0-5

	Working hours		
	(1)	(2)	(3)
Constant	38.64*** (0.07)	38.24*** (0.07)	39.48*** (0.07)
Partner: Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic	0.00 (0.00)	0.00 (0.00)	0.01*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic	0.02*** (0.00)	0.01*** (0.00)	0.02*** (0.00)
Partner: Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic	0.02*** (0.00)	0.01*** (0.00)	0.02*** (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			-0.0 (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			-0.0 (0.00)
Partner: Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			-0.0 (0.00)
Pot. hrs remote work \times Time rel. treat. == -1 \times Pandemic		0.01** (0.00)	-0.02*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 1 \times Pandemic		0.03*** (0.00)	0.02*** (0.00)
Pot. hrs remote work \times Time rel. treat. == 2 \times Pandemic		0.03*** (0.00)	0.02*** (0.00)
Pot. commuting gains \times Time rel. treat. == -1 \times Pandemic			0.01*** (0.00)
Pot. commuting gains \times Time rel. treat. == 1 \times Pandemic			0.00** (0.00)
Pot. commuting gains \times Time rel. treat. == 2 \times Pandemic			0.00*** (0.00)
Time rel. treat. == -1	0.69*** (0.03)	0.69*** (0.03)	-0.2*** (0.03)
Time rel. treat. == 1	0.65*** (0.02)	0.95*** (0.03)	0.49*** (0.03)
Time rel. treat. == 2	1.38*** (0.03)	1.88*** (0.04)	1.28*** (0.03)
Pandemic	1.44*** (0.03)	1.70*** (0.04)	0.51*** (0.04)
Time rel. treat. == -1 \times Pandemic	-0.49*** (0.03)	-0.55*** (0.05)	0.33*** (0.04)
Time rel. treat. == 1 \times Pandemic	-1.15*** (0.03)	-1.42*** (0.04)	-0.95*** (0.04)
Time rel. treat. == 2 \times Pandemic	-1.62*** (0.03)	-1.92*** (0.04)	-1.31*** (0.04)

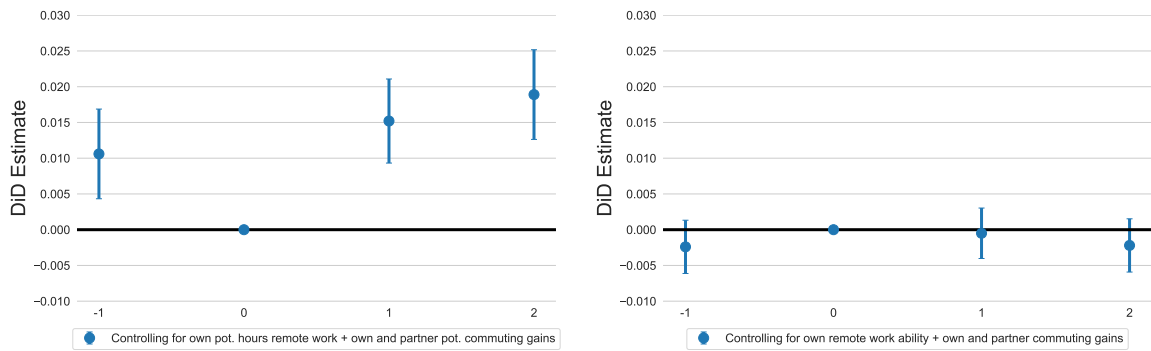
	(0.04)	(0.05)	(0.05)
Pot. hrs remote work		0.13***	0.12***
		(0.00)	(0.00)
Pot. hrs remote work × Pandemic		-0.03***	0.01***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == -1		-0.0	0.02***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == 1		-0.03***	-0.02***
		(0.00)	(0.00)
Pot. hrs remote work × Time rel. treat. == 2		-0.05***	-0.04***
		(0.00)	(0.00)
Partner: Pot. hrs remote work	-0.06***	-0.1***	-0.09***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Pandemic	-0.02***	-0.01***	-0.02***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == -1	-0.01**	-0.0*	-0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == 1	-0.01***	-0.0	-0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. hrs remote work × Time rel. treat. == 2	-0.02***	-0.0	-0.01***
	(0.00)	(0.00)	(0.00)
Partner: Pot. commuting gains			-0.02***
			(0.00)
Partner: Pot. commuting gains × Pandemic			-0.01***
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == -1			0.00
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == 1			0.01***
			(0.00)
Partner: Pot. commuting gains × Time rel. treat. == 2			0.01***
			(0.00)
Pot. commuting gains			-0.02***
			(0.00)
Pot. commuting gains × Pandemic			-0.0***
			(0.00)
Pot. commuting gains × Time rel. treat. == -1			-0.01***
			(0.00)
Pot. commuting gains × Time rel. treat. == 1			0.00***
			(0.00)
Pot. commuting gains × Time rel. treat. == 2			0.01***
			(0.00)
N children == 2	0.26***	0.20***	0.15***
	(0.02)	(0.02)	(0.02)

N children == 3	0.12*** (0.02)	0.04* (0.02)	0.03 (0.02)
N children == 4	-0.17*** (0.06)	-0.14** (0.06)	-0.03 (0.06)
N children >4	-0.14 (0.16)	0.06 (0.15)	0.14 (0.15)
Age	-0.05*** (0.00)	-0.05*** (0.00)	-0.04*** (0.00)
Partner: Age	-0.01*** (0.00)	-0.04*** (0.00)	-0.05*** (0.00)
Youngest child age	0-15	0-15	0-15
Observations	2,593,590	2,593,590	2,471,927
R^2	0.01	0.021	0.022

Notes: The table displays the coefficients of the event-study DiD pooled for fathers with a youngest child below 6. The first column includes only the partner remote work capability. The second column includes both the own and the partner remote work capability. The third column includes both the own and the partner remote work capability and the own and partner potential commuting gains. Remote work capability is 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 share 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. The exact procedure of the variable generation and pooling is described in Section 4.2. 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.



(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 B.8. Complete regression results for fathers can be found in table B.10.