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Hours and income dynamics during the Covid-19 pandemic: The case of the Netherlands[☆]

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A B S T R A C T

Using customized panel data spanning the entire year of 2020, we analyze the dynamics of working hours and household income across different stages of the Covid-19 pandemic. Like many other countries, during this period, the Netherlands experienced a quick spread of the SARS-CoV-2 virus, adopted a set of fairly strict social distancing measures, gradually reopened, and imposed another lockdown to contain the second wave. We show that socioeconomic status is strongly related to changes in working hours, especially when strict economic restrictions are in place. In contrast, household income is equally unaffected for all socioeconomic groups. Examining the drivers of these observations, we find that pandemic-specific job characteristics (the ability to work from home and essential worker status) help explain the socioeconomic gradient in total working hours. Household income is largely decoupled from shocks to working hours for employees. We provide suggestive evidence that large-scale labor hoarding schemes have helped insure employees against shocks to their employers.

1. Introduction

Beginning in early 2020, the Covid-19 pandemiccc has strongly affected working lives around the world. A large number of studies have tracked the crisis' initial impact in the US and European countries on employment, hours worked, and income.[1] Along these dimensions, existing inequalities were generally exacerbated early in the crisis, although the degree varied widely across countries. The fact that inequalities went up is not surprising in light of the particularities of this pandemic-induced recession—e.g., social distancing behaviors, non-pharmaceutical interventions to reduce the virus' spread, or the huge increase in working from home. The first months of the pandemic were, however, also characterized by a substantial amount of uncertainty and by supply chain disruptions (e.g. Meier and Pinto, 2020). Neither is it well understood how employment, hours, and income developed throughout the first year of the pandemic; nor why variations across countries are so large.

We add to this understanding by providing an in-depth analysis of individual labor market trajectories throughout 2020 in the Netherlands, a stereotypical Northwestern European country along many core dimensions.[2] The Dutch government imposed a lockdown from March to May 2020, which was followed by re-opening most parts of the social and economic life over the summer. A second wave of the pandemic led to another lockdown in autumn and winter. Business closures were accompanied by labor hoarding schemes for the employed and various subsidies for the self-employed. Government restrictions and changes in consumer behavior directly affected firm demand; labor supply may be affected by fear of infection or childcare needs.

We make use of customized panel data collected for seven periods during the year 2020 in the LISS panel, a high-quality online survey based on a probability sample of the Dutch population. Doing so allows us to access a wealth of background characteristics from prior years in

☆ The data collection was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) under Germany's Excellence Strategy – EXC 2126/1 – 390838866, by the Dutch Research Council (NWO) under a Corona Fast track grant (440.20.043), and by the IZA – Institute of Labor Economics. Gaudecker and Zimpelmann are grateful for financial support by the German Research Foundation (DFG) through CRC-TR 224 (Project C01). This research would not have been possible without the help of many others at the CoViD-19 Impact Lab, a research group initiated in Bonn in Mid-March 2020. Special thanks to the team at CentERdata, who made the surveys underlying this research possible in record time. We would like to thank Egbert Jongen for very helpful comments. This paper updates and supersedes von Gaudecker et al. (2020b) and von Gaudecker et al. (2020a).

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[1] Examples include Adams-Prassl et al. (2020), Alstadsæter et al. (2020), Eurofound (2020), Coibion et al. (2020), Brynjolfsson et al. (2020), Farré et al. (2020), Bick and Blandin (2020), Crossley et al. (2021), von Gaudecker et al. (2020b), Meekes et al. (2020), Béland et al. (2020).

[2] The Netherlands is fairly similar to countries such as Germany, Denmark, etc. in terms of the social safety net and labor protection laws; the reaction to the pandemic was broadly comparable.

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addition to contemporaneous measures of labor market outcomes and potential drivers thereof.

We document three stylized facts regarding the trends in employment, hours worked, and household income throughout the year 2020. First, the rates of unemployment and non-employment rose by 1.1 and 1.9 percentage points, respectively, between February and May. The unemployment rate slightly decreased thereafter while the rate of non-employment remained constant. Both of these patterns are consistent with administrative records, highlighting the quality of our data. The decrease in employment relationships is much smaller than in many other countries. For example, the US unemployment rate rose by 10 percentage points and labor force participation fell by 4 percentage points between February and April (Bick and Blandin, 2020) and in Canada employment fell by about 15 percentage points (Lemieux et al., 2020).

Second, working hours declined strongly among those who were working just before the pandemic started to affect labor markets. Considering the extensive and intensive margin jointly, hours had dropped by 15 percent on average by April. They stayed roughly at this level for the rest of 2020—aggregate changes were within the realm of seasonal fluctuations. This pattern is very different when breaking down the evolution of working hours by socioeconomic group, measured by education and personal income. Less educated or low-income individuals reduced working hours roughly twice as much as others. This socioeconomic gradient becomes smaller during the summer when infection rates were low and social-distancing restrictions were more relaxed. Again, these facts are consistent with administrative microdata covering the first half of 2020 (Meekes et al., 2020). The initial impact on aggregate working hours is only about half of what Lemieux et al. (2020) find for Canada, but the heterogeneity in the effect is comparable to their findings. During the second lockdown in December, the gradient becomes steeper again but stays below its spring levels. Throughout the year, the evolution of hours worked from home by socioeconomic group tracks the differential evolution of total hours worked.

The third stylized fact is that the distribution of household income hardly changed throughout 2020. Relative to household income in the pre-pandemic months, the median of subsequent changes is zero. This is true across different socioeconomic groups, whether these are measured by education, personal income, or long-run household income. Across these groups, the first and third quartiles of changes in household income are very similar and of limited magnitude. These patterns stand in contrast to the experiences of countries like the UK, where household earnings around the median decreased by 15 percentage points between February and May and poorer households were affected much stronger (Crossley et al., 2021). Their earnings measure includes transfers made through the furloughing scheme; its dynamics should be similar for most parts of the income distribution to our comprehensive measure of income. Similarly, earnings decreased for almost 40 percent of the US population until April (Bick and Blandin, 2020) and vulnerable groups were hit much more strongly (Fazzari and Needler, 2021). Losses were, however, more than compensated by direct transfers from the unemployment insurance system which had a (temporary) replacement rate above pre-pandemic earnings for the lowest income groups (Cortes and Forsythe, 2020; Ganong et al., 2020). Other international comparisons are difficult to make due to different conventions of including transfer payments and different income measures or non-representative sampling. Overall, the picture that emerges is mixed, with some countries experiencing median income losses (e.g., Italy and Spain) and some countries having more stable household income dynamics (Germany, France, and Sweden, see, e.g., Bounie et al., 2020; Clark et al., 2021). Unlike our results, most countries surveyed in this literature experienced some form of heterogeneity in the income response, either by age or education (see, e.g., Belot et al. (2020) for China, Japan, Korea, Italy, UK, US; Osterrieder et al. (2021) for Thailand, Malaysia, UK, Italy, Slovenia), but only some countries had regressive effects on the lowest income groups, such as France (Bounie et al., 2020) and Italy (Belot et al., 2020).

We then leverage our panel data and the tailor-made questionnaires to examine the drivers of these observed trends. During the initial lockdown, essential worker status and the fraction of work that can be done from home explain most of the socioeconomic gradient in total hours worked.[3] The two characteristics interact strongly: telecommutability only plays a role for non-essential workers. In September—when infection rates were low and restrictions on social and economic life were few—these pandemic-specific mechanisms do not play a role and there hardly is a socioeconomic gradient in hours worked. Their importance is large again in December, but weaker than in early spring. These patterns suggest that the best way to ameliorate the socioeconomic gradient inherent in the pandemic's impact on labor markets is to keep infection rates low.

Finally, we relate changes in household income to employment transitions and hours changes using a set of quantile regressions. The median change for employees who remain employed throughout the year is very close to zero throughout. The first quartile of changes is between −7 and −13 percent, whereas the third quartile is between 13 and 17 percent. There is no relation with hours worked. By contrast, the first quartile of the distribution of household income innovations is a loss of about one quarter for the self-employed, for those who become unemployed, and for those who drop out of the labor force. The median is clearly negative for the three groups as well. For those who become unemployed, losses at the third quartile are still 14 percent.

Compared to other countries, separations to non-employment are very low in the Netherlands. The perfect insurance against changes in hours worked for employees that we just described is very rare. We thus run another set of quantile regressions of household income on employment transitions and whether employers' took up the wage subsidy scheme (NOW), which required to continue paying the full wage. Across quartiles, employer take-up of policies is unrelated to household income, suggesting that the combination of firing restrictions and large-scale support policies helped insure employees very well against the fallout of the crisis. The self-employed were hit much harder; the first quartile of those who benefited from any program targeting the self-employed saw their households' income drop by around 70%.

The next section describes the setting for our analysis and the data we collected. In Section 3, we distill the stylized facts on the evolution of employment, hours of work, and household income throughout the first year of the pandemic. We examine the drivers of the dynamics in working hours and household income in Section 4 before concluding in the last part.

2. Context

The following section provides an overview of the development of the Covid-19 spread in the Netherlands and the social distancing policies. We moreover describe the key features of the Dutch labor market and economic support programs and present the data used in the empirical analysis.

2.1. Spread of Covid-19 and social distancing policies

Fig. 1 displays the development of confirmed SARS-CoV-2 infections in the Netherlands on a logarithmic scale (left axis). By mid-March, when we collected our first wave of data, more than 10 new cases per million inhabitants were confirmed each day. This number reached 60 by the end of March and stayed roughly at that level for the first three

[3] Béland et al. (2020) show that early in the pandemic the ability to work from home and essential worker status mitigate labor market impacts in the US. We expand that analysis to a country where labor outcomes are mostly affected on the intensive margin and look at the relevance of these characteristics over different stages of the pandemic.

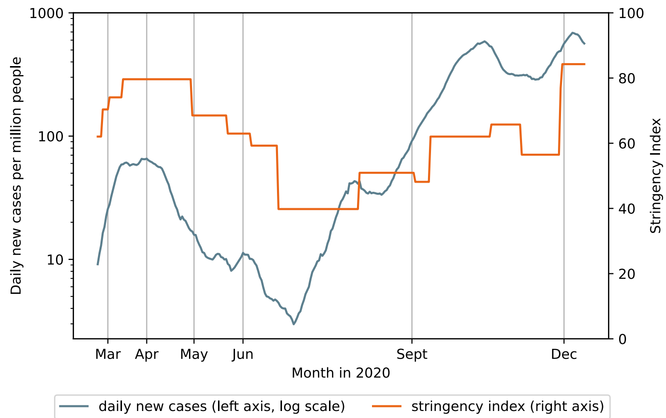


Fig. 1. Daily new confirmed cases per million people and response stringency. *Notes:* The left axis (blue line) shows daily new cases as rolling 7-day average, based on (Roser et al., 2020). The Oxford Response Stringency Index (right axis, orange line) measures the stringency of restrictions on economic and social life (Hale et al., 2020). The vertical lines indicate the waves of data collection (see Section 2.3). They are located at our sample's median response dates for each wave: March 22, April 14, May 12, June 10, September 18, and December 17. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

weeks of April.[4] The incidence measure declined thereafter and reached 10 in mid-May, remaining at that level or somewhat below over the summer. In August, the infection numbers started rising again, reaching a temporary peak of 500 daily new cases per million inhabitants at the end of October. After falling below 300, confirmed infection numbers reached their 2020 peak at 700 new cases just before Christmas.[5]

Similar to other countries, the initial rise in infections prompted the Dutch government to impose restrictions on economic and social life to stop the spread of SARS-CoV-2. The Oxford Response Stringency Index measures the stringency of these policies (Hale et al., 2020) and is shown in Fig. 1 on the right axis. In mid-March, all schools and childcare facilities were closed along with restaurants, cafes, bars, and several other businesses involving personal contacts. People were advised to stay at home, to keep a distance of at least 1.5 m to each other, and to avoid social contacts; the number of visitors at home was restricted to a maximum of three individuals. While most of the policy measures resembled those of other European countries, they did not involve a general curfew and some measures were more lenient. For instance, businesses such as stores for clothes, utilities, or coffee shops remained open as long as they could guarantee to maintain the social distancing rules. Public locations were accessible and traveling or the use of public transportation was possible throughout this lockdown period.

Beginning in May, the restrictions were gradually lifted. Daycare facilities and primary schools started opening in mid-May, businesses such as hairdressers and beauty salons were allowed to accept customers again. In early June, secondary schools started opening; restaurants, cafes, and cinemas could operate under restricted capacity. With the main exceptions of bans on larger (inside) gatherings, the requirement to wear masks in public transport, and the mandate to keep a distance of 1.5 meters to other people, social and economic life was largely back to what it was before.

In reaction to the increasing infection numbers during the fall, the Dutch government successively sharpened the restriction on September 30th, October 14th, and November 4th. The latter set of rules was similar to the one during the first lockdown in spring with the exception that schools were still open. Since the infection rate decreased in the first half of November, the Dutch government decided to lift the restrictions somewhat from November 18, but put an even stricter lockdown into place one month later. This implied that all sports locations, eating locations including room services in hotels, and shops, except supermarkets and essential services, had to close. Moreover, all schools switched to online teaching, and childcare facilities were closed.

2.2. Institutions and ad-hoc economic support measures

The Netherlands is a generic Western European welfare state. There is compulsory social insurance; unemployment insurance is obligatory for employees; and strong labor protection laws make firing employees without cause difficult for employers. To reduce the impact of the lockdown and behavioral reactions to the virus spread on the labor market, the Dutch government implemented several measures starting in mid-March 2020 for the period March to May. These programs were extended with minor adjustments and are in place until at least June 2021.

The first two emergency programs for the Dutch economy amount to about 30 billion Euros, which is about 3–4 percent of the Dutch GDP. The additional fiscal spending relative to GDP due to Covid-19 has been lower in the Netherlands than in other, larger economies such as Germany, UK, and the US; it has been similar to, for example, Sweden or Norway (IMF, 2021).

The most important policy measure targeting employees is the short-term allowance (Noodmaatregel Overbrugging voor Werkgelegenheid, NOW), which subsidizes labor hoarding. Internationally, job retention schemes can be classified into two different types (OECD, 2020): short term work schemes, as introduced in e.g. Germany, the UK or Japan, and wage subsidies as in e.g. Canada or Poland. NOW is classified as a hybrid scheme according to this definition, as employment subsidies were tied to employment guarantees. Under the NOW scheme, the Dutch government supports all businesses that expect a loss in gross revenues of at least 20% between March 2020 and July 2021 with advanced money for labor costs. The amount of advancement depends on the expected revenue loss. A business that expects a loss of 100% can request 90% of its labor costs from the government. The advancement is paid out at three points in time, with a first chunk being paid within 2–4 weeks after a positive decision on the request. Employers who get the advancement commit to paying full salaries to their employees and not fire employees due to reduced business activities. Only Denmark had a similar wage "top-up" requirement (OECD, 2020). Moreover, employers can revert dismissals that already have taken place. The advancement can also be requested for employees with fixed-term contracts or temporary workers. In contrast to labor hoarding arrangements in other countries, e.g. the UK or Germany, affected employees are not required to reduce working hours and their incomes remain the same by default.

The TOZO (Tijdelijke Overbruggingsregeling Zelfstandig Ondernemers, Temporary Bridging Measure for Self-employed Professionals) is the most relevant program for the self-employed. This income support measure was not means-tested in the first three months of existence. For the period June-December, a household-level income test was introduced. Another program for the self-employed is the TOGS (Tegemoetkoming Ondernemers Getroffen Sectoren Covid-19, Reimbursement for Entrepreneurs in Affected Sectors Covid-19), a one-time payment of 4000€ that is conditional on the sector being affected directly by the pandemic or pandemic-related measures between March and May. Further relief was provided through tax deferrals and loan guarantees for firms. We provide some more detail in Table A.2 of the Online Appendix.

[4] The peak in daily cases was also between 60 and 70 in Germany, France, or the UK, although the plateau lasted shorter in Germany and France. It lasted much longer in the UK. During the March-April period, the peaks were substantially higher in Spain (160), Italy, and the US (both between 90 and 100).

[5] These numbers include only confirmed cases. Since testing increased over time, the numbers are not directly comparable. The test positive rate peaked at 27% in late March but was about 5 % in September before increasing again to 16 % thereafter.

2.3. The LISS panel

To understand the behaviors and expectations of households during the different stages of the Covid-19 crisis, we designed a set of modules in 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 consists of roughly 4000 Dutch households comprising about 7000 individuals. It is administered by CentERdata, a survey research institute affiliated with Tilburg University, the Netherlands, and has been used in several studies on individual and household behavior (e.g., Cherchye et al., 2012; 2017; Drerup et al., 2017; Noussair et al., 2014).

The first module of our questionnaire was fielded between March 20th and 31st 2020, a few days into the lockdown. Five more modules followed throughout April, May, June, September, and December. With roughly 80%, the response rate was at the top end of the span of usual response rates in the panel for all waves. Throughout this paper, we restrict our sample to respondents aged 18 to 66 years where the latter is the legal retirement age in the Netherlands in 2020. Whenever not stated otherwise, we furthermore restrict on all individuals working at least 10 h before the pandemic. This leaves us with 17,314 observations over all waves. While the resulting panel is unbalanced, the distribution of demographic variables is very stable over time.[6]

Our questionnaires ask respondents about working hours at home and at the workplace during the last week. To assess the effect of the pandemic on labor supply in certain jobs, we elicit two job characteristics that are potentially important for labor supply during contact restrictions. First, we ask all subjects working before Covid-19 if their job qualifies as essential to the working of public life. Altogether, 35% of respondents work in an essential job. Second, in the May and December questionnaire, we ask about the fraction of usual work that can be done from home. In May, the question explicitly referred to the period before the pandemic. We find that the measure is very stable between May and December, both on the individual level and based on the aggregate distribution.[7] We, therefore, take the mean of the two elicitations. On average, 44% of all tasks can be done from home. The measure varies across the whole distribution; the first quartile is zero and the third quartile is 90%.[8] Furthermore, we ask for household income every month during the pandemic. This allows us to examine how changes in working hours translate to the financial situation of households and how inequality is affected.

All questions are documented in von Gaudecker et al. (2021). Questionnaires of the LISS panel from 2019 and the first months of 2020 provide us with a rich set of additional background characteristics.

3. Work and income in 2020

To analyze the impact of the crisis on inequality within society, we document how changes in working hours and household income are related to the socioeconomic status, measured by education, personal income, and household income.

3.1. Aggregate employment and working hours

While GDP contracted by 9.3% year-to-year in the second quarter of 2020, the non-employment rate and unemployment rate increased only slightly by roughly 1.1 and 1.9 percentage points each (more details in Section Appendix C in the Online Appendix). The unemployment rate slightly decreased thereafter while the rate of non-employment stayed at this level.[9] These aggregate movements in the labor market are fairly similar to the movements experienced by countries such as Germany or the UK; they are less extreme than in Southern Europe or the US (see e.g. Anderton et al., 2020; Coibion et al., 2020; Crossley et al., 2021).

To analyze the impact of the pandemic on the labor market, our main focus is on the dynamics of working hours. In a country like the Netherlands, with strong labor protection laws and comprehensive support policies implemented during the pandemic, focusing on job separations misses a large part of the effects of the crisis. As argued above, job separations were low even though aggregate output decreased substantially. To examine the extent and heterogeneity of productivity losses, it is, thus, vital to investigate the intensive margin, i.e. changes in working hours. Therefore, we analyze the dynamics of relative changes of unconditional working hours. This approach captures both the extensive (flow out of employment) and intensive margin of employment shocks.

From the workers' perspective, there are at least two reasons why reductions in working hours matter even if they do not loose their job. First, labor hoarding may not be sustainable in the medium term (the Dutch programs, for example, only ran for a few months and were renewed multiple times). A negative shock to working hours would then be an early indicator of future employment loss. This is certainly what respondents in our sample believe on average; working hours reductions are predictive of higher job loss expectations (Appendix C.4). Second, working fewer hours might reduce the accumulation of human capital and delay future wage growth. This seems particularly plausible for recent job entrants.

The first row of Table 1 shows aggregate weekly unconditional working hours for each observed period. As we asked for the pre-Covid-19 working hours retrospectively, both, in March and April, the number of observations is higher for this period.[10] Working hours initially decreased by 4.3 h or 12%. They bottomed out in May at a decrease of 7.7 weekly hours and rose thereafter by 2.5 h until December. Based on the Dutch labor force survey (EBB), the drop in conditional working hours until April was 3 h which is as expected slightly smaller than the changes in unconditional working hours in our sample (CBS, 2020). The EBB also shows that in the last years, working hours tended to be up to 3 h larger in December than in May, June, and September. This might explain the increase in working hours despite increasing infections during the last wave of our data.

The most striking change in the labor market has been an unprecedented rise in the amount of work performed from home. Indeed, the second row of Table 1 shows a huge jump in March from 4 to over 15 h until April. The share of hours worked from home increased from 11% to 50% in the aggregate. This fraction declined steadily to 31% in September before increasing again in December. The joint patterns of total hours and home office hours display the starting point of this paper: The pandemic led to both an increase in home office hours and a

[6] For brevity, we present descriptive statistics of our data in Section Appendix B of the Online Appendix.

[7] We would expect larger differences if we had also asked about telecommutability before the pandemic started. It is likely that many people only realized how much they could actually work from home in March/April.

[8] The measure is with a correlation of 0.82 highly correlated between both points in time. For more information on the distribution and reliability of the measure, consult Appendix B.3.

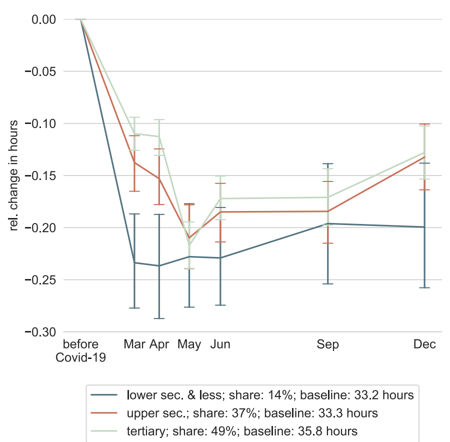
[9] In official data by Statistics Netherlands, the level of un- and non-employment is somewhat lower, but the development over time overall lines up well with the numbers in our sample. We present a comparison to official data, visualizations of observed aggregate patterns, and robustness analyses of those patterns in Section Appendix C in the Online Appendix. Robustness analyses include sample weights and an alternative before-Covid-19 measure that uses the time use and consumption survey conducted in November 2019.

[10] A potential concern is that observed changes in working hours might be driven by the baseline being asked retrospectively. An alternative baseline measure is based on the time use and consumption survey that was in the field in November 2019. As participants are in this study also asked for their working hours in the last week, the elicitation method is closer to the one for our observations from March on. Appendix C.2 shows that the distributions of both measures are closely aligned. Given that this alternative baseline was elicited longer before the pandemic and the joint sample is substantially lower, we rely on the retrospective measure from March/April 2020 for our analyses.

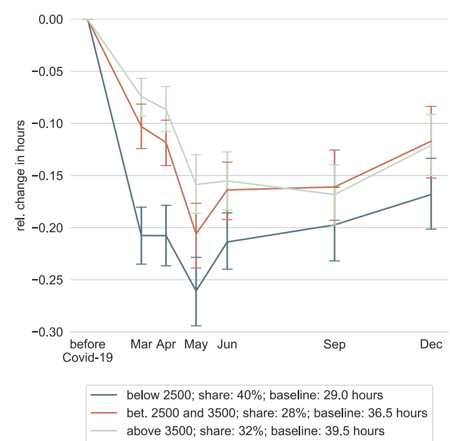
Table 1
Unconditional working hours over time.

	before Covid-19	Mar	Apr	May	Jun	Sep	Dec
working hours	34.5	30.2	29.5	26.8	27.9	27.8	29.3
	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
N	2962	2656	2634	2375	2518	2384	2298
hours worked from home	4.1	15.0	15.5	12.3	11.2	8.9	12.0
	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
N	2962	2656	2634	2375	2518	2384	2298
share of hours worked from home	0.11	0.49	0.51	0.45	0.38	0.31	0.39
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	2962	2437	2408	2106	2317	2127	2052

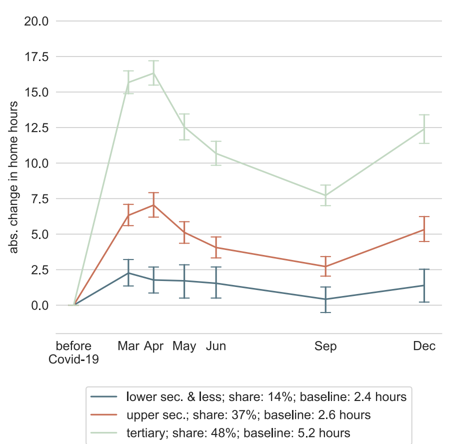
Notes: The first two rows present unconditional total working hours and hours worked from home over time. All statistics are on respondents between ages 18 and 66 who worked for at least 10 h in early March. The share of hours worked from home is only defined for individuals working in that period. Source: LISS.



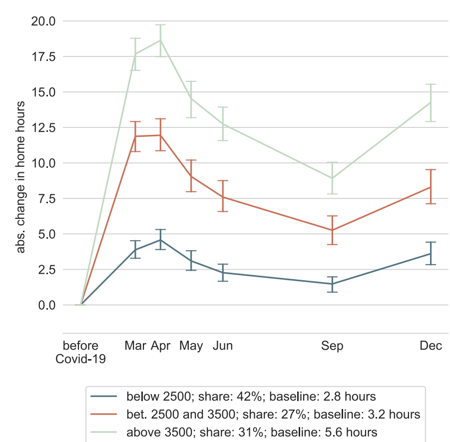
(a) Relative change in total working hours by education



(b) Relative change in total working hours by personal income



(c) Change in hours worked from home by education



(d) Change in hours worked from home by personal income

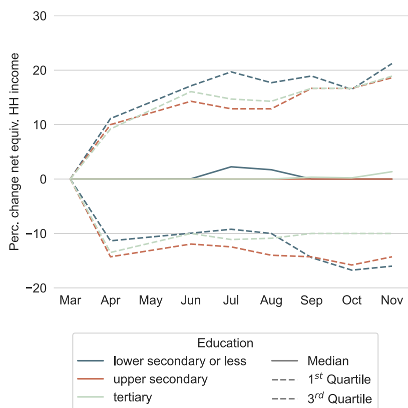
Fig. 2. Mean changes in total working hours and hours worked from home, by socioeconomic status. *Notes:* The top row shows mean relative changes in total hours worked by achieved education level (Fig. 2a) and by personal gross income in three categories (Fig. 2b). Fig. 2c and d display mean absolute changes in hours worked from home for the respective groups. Reference period is late February/early March. The legend displays hours and share of each group in early March. Vertical bars depict 95 %-confidence intervals. Sample: 18 $\leq$ age $\leq$ 66; working hours of at least 10 h in early March.

decrease in total working hours in March and April. The former quickly became much less important as infections dwindle and restrictions were lifted, while the overall amount of work stayed much lower than before the crisis.

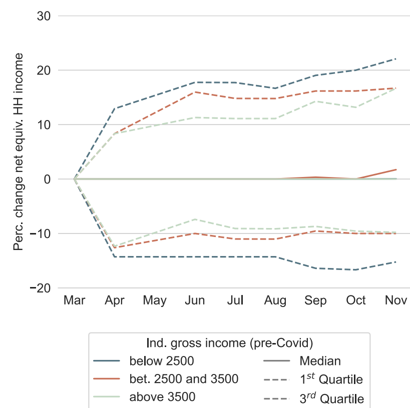
3.2. Inequality in working hours and in working from home

Similar to studies for the US and UK, we find that the impact on hours is highly unequally distributed among socioeconomic groups. The top row of Fig. 2 displays relative changes of total working hours, relative to early March 2020, by level of education (Fig. 2a) and personal gross income (measured before the pandemic; Fig. 2b). For individuals with lower secondary education or less, working hours fell by more than 22% on average in March and April. Better educated subjects reduced working hours significantly less: for those who completed tertiary education the reduction was just 11%. This difference becomes smaller in later months when restrictions were lifted before increasing again in December. Fig. 2b shows that income is also predictive of changes in working hours: the group of individuals earning less than 2500 Euros reduced total working hours by more than 20% on average during March and

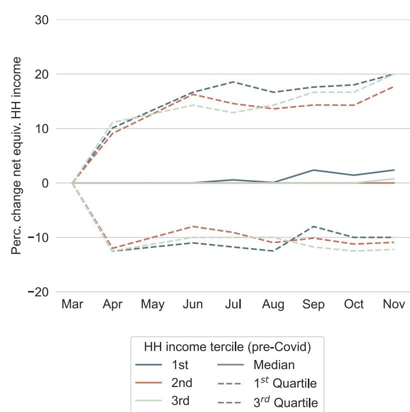
Fig. 3. Relative changes in net equivalized household income by socioeconomic status. *Notes:* Relative change of net equivalized household income relative to the average of January and February 2020. Pre-Covid household income tercile calculated by using the terciles of the average household income of 2018 and 2019. Sample: 18 ≤ age ≤ 66, working pre-Covid, report positive household income in either January or February (this excludes 170 individuals). We leave out May because the vacation bonus renders the graphs difficult to read; see Fig. D.6 in the Online Appendix for the same figure including the May numbers.



(a) Relative changes in net equivalized household income by education



(b) Relative changes in net equivalized household income by pre-Covid individual gross income



(c) Relative changes in net equivalized household income by pre-Covid household income

April. This is roughly twice as much as individuals earning more. The difference to the highest-earning group decreases over time but is still roughly 3% in September and December.

The differences for hours worked from home by education (Fig. 2c) are even stronger and more persistent over the full course of the pandemic. While the lowest educated group increased home office hours by less than 2.5 h in all observed months, subjects with tertiary education did so by more than 15 h during the first lockdown and still more than 7.5 h in September. Fig. 2b shows similar patterns for personal income: over the full course of the pandemic in 2020, better-earning individuals work consistently more from home although the level of working from home varies for all groups.

When splitting the sample by pre-crisis household income instead of personal income, the differential effects are substantially weaker indicating that personal characteristics are the main driver for the change in working hours (Fig. D.3 and Table D.2 in the Online Appendix).

In summary, the impact of the pandemic on the amount and location of hours worked differed strongly by socioeconomic status. More educated and better-paid individuals increased hours worked from home much more and decreased total working hours substantially less, the latter especially during the initial lockdown in March and April. We next examine whether these differences also translate into differences in household income during the pandemic.

3.3. Income inequality

In April, June, September, and December, we asked individuals retrospectively about their household income in the previous months. Fig. 3 depicts quantiles of changes in net equivalized household income relative to the average in January and February 2020, by socioeconomic characteristics.[11] Median changes are close to zero in every month between March and November for all values of socioeconomic variables that we condition on. Similar to our analysis of working hours, Figs. 3a and b slice the data by education and individual gross income, respectively. Fig. 3c conditions on pre-Covid household income—measured using LISS core questionnaires for the years 2018 and 2019—as a comprehensive measure of economic means. For all three measures of socioeconomic status, the evolution of the first and the third quartile in changes is rather symmetric around zero. If anything, gains at the third quartile are slightly higher than losses at the first quartile. Again, there is no clear socioeconomic gradient in any of the measures. Hence, we do not see an increase in income inequality in 2020 in the Netherlands. This is in stark

[11] We exclude the month of May because most employees receive a vacation payment mandated by law; the resulting jumps at all quantile make the graph very hard to read. See Fig. D.6 in the Online Appendix for the same graph as Fig. 3 including the May data.

Table 2
Job characteristics by socioeconomic status.

	essential worker	frac. work doable from home
education: lower secondary and lower	0.37	0.17
education: upper secondary	0.40	0.31
education: tertiary	0.32	0.61
gross income: below 2500	0.41	0.29
gross income: bet. 2500 and 3500	0.39	0.45
gross income: above 3500	0.28	0.63

Notes: The table shows for different subsamples by socioeconomic status (left side) the share of the sample that is an essential worker, and the average share of work that can be done from home. Sample: $18 \leq$ age ≤ 66; working hours of at least 10 h in early March.

contrast to, for example, the UK experience. Crossley et al. (2021) show that in May the earnings losses for the lowest quintile of the long-run income distribution were 60% at the first quartile and 13% at the median.[12] For the second-lowest quintile, the respective changes were -36% at the first quartile and - 6% at the median.

4. Explanations and mechanisms

The previous section highlighted three important findings. First, the reduction in working hours is unequally distributed among socioeconomic groups. Second, this seems to be particularly driven by an unequal substitution between working at the workplace and working from home. Third, despite the large and unequal decline in working hours, we do not observe a large and unequal decline in household income. In this section, we explore whether the dynamics in working hours are driven by pandemic-specific features. We then analyze the relation of working hour changes and changes in household income and examine why the socioeconomic gradient for working hours changes does not carry over to household income.

4.1. Working hours

Two job characteristics stand out that are potentially highly relevant during restrictions of economic activity: First, the ability to work from home. Doing so is the most natural way to continue working while keeping a distance from people outside the own household. Second, essential workers were exempted from most restrictions imposed on work lives. Table 2 shows the distribution of these job characteristics over socioeconomic groups. The definition of essential workers was rather wide in the Netherlands and 35% of our sample state they are covered by this definition. This share does not vary strongly with the level of education but is negatively related to income: 40% of individuals earning less than 2500 Euros work in essential occupations while this is the case for only 27% of individuals earning more than 3500 Euros. By contrast, the ability to work from home is strongly positively related to both education and income. In the lowest education category, only 17 % of work can potentially be done from home, while this share is more than three times higher for individuals with tertiary education. These relations suggest that the strong gradient in realized home office hours described in the last section might be reflected in differing potentials to do so.

We next investigate whether pandemic-related job characteristics can explain the observed trajectory of aggregate working hours and especially the socioeconomic gradient. We regress relative changes of working hours on socioeconomic variables, essential worker status, telecommutability, and interaction of these two job characteristics. All regressions control for gender, work status before the pandemic (full-time employed, part-time employed, self-employed), and age. For conciseness, Table 3 focusses on the channels of particular interest and pools observations for the months March-June 2020 and for September/December 2020, respectively. Table D.3 shows the full set of coefficients in a specification with disaggregated time effects and interactions.

Column 1 of Table 3 is the multivariate version of our analysis in the previous section. Not controlling for essential worker status and telecommutability, better educated and high-income individuals reduce their working hours less throughout. The disaggregated analysis (Table D.3) shows that this relation is most pronounced in March/April and December, when the strongest restrictions were in place.

Column 2 of Table 3 adds job characteristics. Conditional on not being able to perform any tasks from home, essential workers' unconditional working hours are 13 percentage points higher than that of similar non-essential workers during the first four months of the pandemic. In September and December, the difference is even smaller and no longer statistically significant. For non-essential workers, moving the degree of telecommutability from zero to one increases average hours by 18 percentage points between March and June. The effect almost disappears during the second half of the year, where the specification hides the fact that it increases to 9 percentage points during the December lockdown (see Table D.3). Importantly, the coefficient on the interaction of these two job characteristics implies that there is no effect of telecommutability for essential workers. Controlling for sector by month fixed effects in Column 3 does not change any of these coefficients in a meaningful way. Any potential spillover effects within sectors thus seem to be limited.

Unsurprisingly, the relation of working hours reductions with socioeconomic variables becomes somewhat weaker once we add essential worker status and telecommutability to the regression (Column 2). This indicates that the heterogeneous effects by income and education can be explained to some degree by pandemic-specific job characteristics. Low-educated individuals seem to reduce working hours more strongly due to their lacking ability to work from home in their current jobs. At the same time, however, the results show that for given job characteristics, higher-earning individuals were more successful in conserving their working hours. One explanation could be that they might have been better able to realize the potential to work from home while employees earning less might more often lack the technical support to do so. Furthermore, pre-pandemic earnings might proxy the robustness of firms towards the Covid-19 shock – especially for self-employed individuals.

In terms of other control variables, females see an extra loss of 4 to 6 percentage points in all months except June and September. These differences cannot be explained by job characteristics. We explore the gendered patterns of employment shocks and childcare in a separate paper, where we also discuss the nature of part-time work in greater detail (Holler et al., 2021). The self-employed are hit very hard initially and see an additional average loss of 13 percentage points during the lockdown period compared to full-time employees. The difference in hours reductions falls to 3 percentage points and is no longer statistically significant in June. This pattern is consistent with many small businesses operating in industries that are hit particularly hard by the restrictions—bars and restaurants, hairdressers, etc.—as well as firms providing insurance to

[12] Earnings are defined as take-home pay and will thus include transfers made under the Job Retention Scheme via the employer.

Table 3
Hours worked by individual and job characteristics.

	change total working hours		
	(1)	(2)	(3)
march-june × education: upper sec.	0.05***	0.03*	0.03
	(0.02)	(0.02)	(0.02)
september/december × education: upper sec.	0.04	0.04	0.03
	(0.03)	(0.03)	(0.03)
march-june × education: tertiary	0.05***	0.01	0.01
	(0.02)	(0.02)	(0.02)
september/december × education: tertiary	0.06*	0.06*	0.06*
	(0.03)	(0.03)	(0.03)
march-june × income bet. 2500 and 3500	0.06***	0.05***	0.03**
	(0.02)	(0.02)	(0.02)
september/december × income bet. 2500 and 3500	0.05**	0.05**	0.03
	(0.02)	(0.02)	(0.02)
march-june × income above 3500	0.09***	0.06***	0.05***
	(0.02)	(0.02)	(0.02)
september/december × income above 3500	0.03	0.03	0.01
	(0.02)	(0.03)	(0.03)
march-june × essential worker		0.13***	0.12***
		(0.02)	(0.02)
september/december × essential worker		0.03	0.04
		(0.03)	(0.03)
march-june × frac. work doable from home		0.18***	0.18***
		(0.02)	(0.02)
september/december × frac. work doable from home		0.02	0.03
		(0.03)	(0.03)
march-june × essential × work doable from home		−0.16***	−0.15***
		(0.03)	(0.03)
september/december × essential × work doable from home		−0.07	−0.08*
		(0.04)	(0.04)
N	15,738	15,738	15,133
R^2	0.151	0.163	0.168
demographic controls	Yes	Yes	Yes
month × sector FE	No	No	Yes

Notes: The table shows OLS regressions of relative changes in total (unconditional) working hours. Reference period = Early March. Further elements of the specifications include a full set of time dummies, gender, and pre-pandemic measures of part-time work and self-employment (all interacted with time dummies). Table D.3 shows the full set of coefficients in a specification with disaggregated time effects and interactions. Standard errors are clustered on the individual level. The data are restricted to individuals who worked at least ten hours in early March. *Notes:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

their employees (Guiso et al., 2005), potentially with the help of the government. Sectoral differences are large during the lockdown but become smaller in later months. All this is consistent with the broad line of our overall results, i.e., the specific features of a pandemic recession becoming less important in the months following the first lockdown.

A potential concern with our data is that pre-pandemic working hours are asked retrospectively for a few weeks earlier while working hours in all other periods are asked for the last week. We, therefore, make two robustness checks: First, we exclude subjects that took a day off out of turn, e.g. because of official holidays, vacation, or being sick. Second, we use the time use survey of November 2019, which also asked for working hours during the last week, as the reference period. Our results do not change substantially (Table D.1 in the Online Appendix).

4.2. Household income

To analyze why the relationship between employment shocks and socioeconomic status does not translate into a similar gradient for changes in net equivalized household income, we regress relative changes in household income on relative changes in working hours and time fixed effects. We use quantile regressions and report results for the three inner quartiles. Compared to OLS regressions, quantile regressions allow us to study effects on household income at several points of the distribution. Furthermore, they are less affected by outliers. To distinguish between the extensive margin (movements out of employment) and the intensive margin (changes in working hours among employed and self-employed), we create multiple mutually exclusive indicator variables. In each period, an individual can either be employed, self-employed, unemployed, or out of the labor force (retired, student, homemaker, receiving social assistance). We consider the employed and self-employed separately if they kept their job. Conversely, we use groups for those who became unemployed and those who dropped out of the labor force, irrespective of whether they were employed or self-employed before the pandemic. If an individual was employed pre-Covid, she is classified as *employed (pre-Covid) ⇒ employed* if she is employed in the respective period; as *empl or self-empl (pre-Covid) ⇒ unemployed* if she is unemployed in the period; as *empl or self-empl (pre-Covid) ⇒ out of labor force* if she dropped out of the labor force. The definition for initially self-employed individuals is equivalent.[13] We leave out March because the working hours information refers to late March only, which will not be representative of the entire month.

The results are displayed in the first three columns of Table 4. The time dummies refer to individuals who remain in employment; for all three quartiles, they are very close to the unconditional quantiles in Fig. 3 in April, but considerably narrower thereafter. Interestingly, changes in working hours do not affect the employed as is evident from the fifth row. Changes in hours refer to working hours in the respective

[13] We drop respondents who transition from employment to self-employment and from self-employment to employment because of the small group size (maximized at 28 individuals in September).

Table 4
Relationship between labor market outcomes, support policies, and household income.

	Dependent variable: Rel. change in net equ. HH income					
	Hours worked			Support policies		
	p25	p50	p75	p25	p50	p75
April	−12.5***	0.00	13***	−10***	0.41	13.28***
	(1.01)	(0.01)	(1.03)	(1.37)	(0.54)	(1.45)
May	−4.05***	7.14***	44.44***	−2.17	7.31***	44.87***
	(1.23)	(0.95)	(2.13)	(1.33)	(1.05)	(2.32)
June	−7.41***	0.09	15.79***	−6.25***	0.41	15.89***
	(1.04)	(0.48)	(1.03)	(1.08)	(0.63)	(1.14)
September	−8.56***	1.35*	16.76***	−7.94***	1.54**	16.73***
	(0.97)	(0.71)	(1.32)	(1.16)	(0.73)	(1.38)
rel. change in work. hours × employed (pre-Covid) ⇒ employed	0.07	0.00	−0.01			
	(0.58)	(0.21)	(1.67)			
Policy: Yes × employed (pre-Covid) ⇒ employed				0.16	−0.41	−2.16
				(1.54)	(0.59)	(2.43)
Policy: I don't know × employed (pre-Covid) ⇒ employed				−4.58***	−0.41	1.13
				(1.59)	(0.58)	(2.05)
self-empl (pre-Covid)⇒ self-empl	−25.82***	−7.14**	−3.2	−19.76***	−5.92**	−3.05
	(3.34)	(3.17)	(4.81)	(3.11)	(2.76)	(4.33)
rel. change in work. hours × self-empl (pre-Covid) ⇒ self-empl	−2.06	−2.94	−4.15			
	(3.16)	(15.35)	(13.23)			
Policy: Yes × self-empl (pre-Covid) ⇒ self-empl				−51.49***	−10.48	4.06
				(14.87)	(9.05)	(11.07)
empl or self-empl (pre-Covid) ⇒ unemployed	−26.52***	−16.04***	−14.44**	−29.08***	−19.28***	−14.73**
	(7.14)	(5.81)	(6.92)	(7.79)	(5.55)	(6)
empl or self-empl (pre-Covid) ⇒ out of labor force	−24.77***	−7.14**	−4.76	−25.1***	−7.31***	−4.73
	(4.87)	(2.82)	(6.37)	(4.59)	(2.06)	(5.74)
N		8595			8564	

Notes: Quantile regressions with relative changes in net equalized household income (relative to the average of January and February 2020) as the dependent variable. Standard errors are clustered on the household level using the wild bootstrap procedure proposed by Hagemann (2017) and implemented in the R package quantreg. Sample: 18 ≤ age ≤ 66; employed or self-employed while working at least 10 h pre-Covid (early March); positive household income either in January or February 2020 (this excludes 170 individuals). Reference group: employed (pre-Covid) ⇒ employed. Policy: Yes = respondent's employer/respondent applied for policy support and was not rejected; "I don't know" = respondent does not know whether employer applied for support policies. For employed only the NOW policy was considered. For self-employed, all potential policies were considered.

month relative to working hours in late February/early March. All three coefficients are zero and precisely estimated. Unsurprisingly, the lower tail looks much worse for the self-employed, where the evolution of the first quartile implies an additional loss of 25% of pre-Covid household income relative to those who remain employed. At the median, the additional drop is 7%; it is smaller and insignificant for the third quartile. The point estimates for hours changes go in the opposite direction as the expected co-movement of hours and income, but these are estimated very imprecisely. The last two rows show that the magnitudes of changes in household income of individuals who transitioned from working to not working are similar to the self-employed who remain so. For those who become unemployed, point estimates are larger at the median and the third quartile. The effects of extensive margin adjustments on household income are likely similar to changes in household income of those who remain in self-employment because transitions out of work are more frequent for part-time workers. This leaves many households where one partner worked part-time the primary earner's income. Similarly, high replacement rates from unemployment insurance or pensions will often be higher for part-time workers with relatively low incomes.

In the second set of columns of Table 4, we replace changes in working hours with an indicator of whether individuals received any policy in case they continue to work. For individuals who become unemployed or drop out of the labor force, we do not make a distinction whether they benefitted from any policy before.[14] Unsurprisingly, their coefficients look very similar to those in columns 1–3; so do the coefficients on the time dummies. The most interesting results are those for the employed, where we only consider the NOW (labor hoarding) program. There are no significant differences in the innovations to household income conditional on policy receipt or not, except for a small drop at the first quartile for individuals who do not know whether their employer applied for the NOW. Although we lack a precise counterfactual for what would have happened in absence of this policy, the experience in other countries suggests that incomes would likely have dropped with hours reductions for employees.[15] For the self-employed, we see much larger reductions in household income if they made use of any support policy. This is an indicator that the programs seem reasonably well-targeted. Altogether, the results from the regressions including support policies suggest that the NOW achieved its goal of near-perfect insurance against changes along the intensive margin for employees. Given the low numbers of separations into non-work relative to many other countries, they are likely to have helped in limiting these transitions, too.

5. Conclusion

This study has analyzed how the Covid-19 pandemic affected the Dutch labor market over the entire year 2020. Compared to countries like the US (Bick and Blandin, 2020), much fewer job separations occurred, but working hours were substantially affected. We show that subjects with lower socioeconomic status faced the strongest decreases in working hours. At the same time, their hours worked from home increased only slightly. This heterogeneous effect did not translate to a socioeconomic gradient in household income changes.

Examining the drivers of these patterns, we find that pandemic-specific job characteristics (telecommutability and essential worker sta-

[14] Remember from Section 2.2 that in total, both rows contain less than 3% of individuals at any point in time.

[15] Figure D.1 in the Online Appendix shows that policy take-up was strongly related to reductions in working hours for both employees and the self-employed.

tus) are highly predictive of working hours changes while social distancing restrictions are in place. We stress the interaction of those two job characteristics: home office capability only mattered for changes in working hours of non-essential workers. When case numbers are low and economic restrictions are widely abolished, these job characteristics hardly influence hours worked. As a consequence, the socioeconomic gradient in employment outcomes was low during the summer albeit working hours were still substantially lower than before the pandemic.

Household income did not decrease in the medium term and was decoupled from employment shocks for individuals who remained employed. This stands in stark contrast to the UK, where the pandemic led to a large negative shock on earnings inclusive of transfers made through the Job Retention Scheme (Crossley et al., 2021). The finding is also very different from the impact of the Great Recession in the Netherlands. Income declined by 13% in 2009 while movements out of employment were similar (van den Berge et al., 2014). It seems likely that the government support programs are responsible for these differences: the NOW program not only aims at job retention but also at full wage insurance for workers. This was not the case for the job retention scheme during the Great Recession in the Netherlands (Hijzen and Venn, 2011). Our explanation is supported by the finding that the take-up of NOW is unrelated to changes in household income. Thus, we provide suggestive evidence that inducing full wage stability through job retention schemes might counteract medium-term regressivities in income better than other work retention schemes. Household income of self-employed subjects was hit particularly hard and could only be partly cushioned by support policies. This likely reflects the fact that it is much harder to design incentive-compatible support measures for the self-employed. It thus is crucial to continue supporting the self-employed during the pandemic and help them to get back to business when infection numbers allow it.

Future research may shed more light on the effects of support policies by comparing household income dynamics to institutionally more similar countries with different job retention schemes not targeting full wages such as Germany. We are not aware of any study that analyzes household income dynamics in 2020 in any other Northwestern European country.

Appendix A. Context

A1. Policies

Table A.1 and Table A.2

Table A.1
Overview government support program to fight the Corona crisis.

program & period	type	eligilibility & content	target group
noodpakket 1.0 March-May 2020	NOW 1.0	• company with at least 20% expected loss in gross revenues relative to actual loss in gross revenue for a 3-month period can request up to 90% of labor costs; maximum labor cost compensation/employee is set to € 9538 which is 2x the maximum “dagloon” (fiscal number to determine social security benefits) • obligation: employer pays 100% of wages to employees; no lay offs for business related reasons • consequence lay offs: fine of 50% of requested subsidy, thus 150% of subsidy has to be paid back • applies to employees with permanent and fixed term contracts • number of working hours is set by an agreement between employer and employee • advance money: 80% of requested subsidy; actual loss in gross revenues is evaluated afterwards and corrected retrospectively (employer either has to pay back or receives additional subsidies); large requests require auditor’s report • reference period: expected gross revenues are compared to revenue from January-December 2019 divided by four (different for companies not existing on Jan 1, 2019). • a compensation of labor costs of 30% has been chosen for all cases (not sure here)	all companies
	TOZO 1.0	• income support program for self-employed; lump sum payments up to social minimum (see https://www.uwv.nl/particulieren/bedragen/detail/sociaal-minimum) • eligibile: businesses founded before March 17, 2020; business was founded before January 1, 2019: minimum number of hours worked is 1225 hrs/a; founded after January 1, 2019: at least 23.5 h/wk • TOZO 1.0: income of partner was not taken into account • self-employed can request loan on business capital (berijfskapitaal); maximum loan: € 10,517 at reduced interest rate to solve liquidity problems	self employed
	TOGS	• direct lump sum payment of *e*4000 to employers particularly affected by the social distancing regulations to fight the Corona crisis	self-employed directly affected by social distancing regulations

Table A.2
Overview government support program to fight the Corona crisis, cont.

program & period	type	eligilibility & content	target group
noodpakket 2.0 June-September 2020	NOW 2.0	• very similar to NOW 1.0, few main differences • expected loss in gross revenues for 4 months; reference period for calculation: March 2020 • compensation for labor costs increases from 30% to 40% • fine for lay offs due to business related reasons is abolished; subsidy is reduced by 5% if companies with 20 and more employees does not request lay off of employees in time (law WMCO) during subsidy period • employer encourages employee to participate in on-the-job-training programs (extra budget) • no pay out of bonuses to management or profits to shareholders, buy back own shares	all companies
	TOZO 2.0	• similar to TOZO 1.0 • main difference: partner income is also taken into account; amount of income support based on social minimum is now calculated on household income rather than individual income	self employed
	TVL (replaces TOGS)	• Compensation for fixed costs from € 1000 up to € 50,000 if loss in gross revenues is more than 30%; minimumn fixed costs: € 4000 • maximum of fixed costs subsidized is 50%; Minimum subsidy per company: € 1000; maximum subsidy: € 50,000 • compensation period: 4 months	applies to micro, small, medium sized companies (MKB). Medium sized companies have less than 250 employees, less than € 50 Mio gross annual revenues, a maximum of € 43 Mio annual balance

Table B.1
Descriptive statistics main sample.

	N	mean	std. dev.	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$
female	2962	0.52				
age	2962	44.24	12.33	34	45	55
education: lower sec. and below	2962	0.14				
education: upper secondary	2962	0.37				
education: tertiary	2962	0.49				
net hh income 18/19 (equiv)	2468	2.39	3.38	1.67	2.18	2.82
full time employed pre-Covid	2962	0.62				
part time employed pre-Covid	2962	0.28				
self-employed pre-Covid	2962	0.10				
gross income	2781	3.71	31.53	1.94	2.87	3.91
essential worker	2962	0.35				
frac. work doable from home	2634	0.44	0.41	0	0.38	0.9
affected by policy: yes	2962	0.16				
affected by policy: no	2962	0.33				
affected by policy: don't know	2962	0.26				

Notes: Source LISS. Household income in thousands. All statistics are on respondents between ages 18 and 66 who worked for at least 10 h in at least one of the 6 periods.

Table B.2
Distribution of work from home capability in December and May.

	count	mean	std	min	25%	50%	75%	max
May	2746	0.45	0.42	0.0	0.0	0.40	0.90	1.0
Dec.	2671	0.44	0.43	0.0	0.0	0.30	0.90	1.0
dev. in meas.	2177	0.01	0.25	−1.0	0.0	0.00	0.02	1.0
abs. dev. in meas.	2177	0.13	0.22	0.0	0.0	0.01	0.18	1.0

Notes: First (second) row displays the distribution of work from home capability in May (December). Third row displays the distribution of the intra-subject changes in answers between May and December. Deviations are calculated by subtracting the May answer from the December answer of subjects. The fourth row displays the distirbution of the absolute value of deviations.

Appendix B. Data

In this part of the appendix, we describe and examine additional aspects of our data and the variables we use.

B1. Descriptive statistics

The first row of Panel A of Table B.1 shows that just over half of our sample is female. Thirteen percent left school with a primary or lower secondary degree (bo/vmbo), 37% have completed upper secondary education (havo/vwo/mbo), just under one half of the workforce has some form of tertiary education (wo/hbo). Before the Covid-19 crisis started, just over a quarter of the sample were employed part-time, defined as working no more than 30 h per week; 62% were in full-time employment while one in ten individuals was self-employed. Individuals' gross monthly income before the crisis was 3710€ on average; median income is at 2870€. We also make use of long-run household income which allows us to examine the impact on inequality. It is measured as the average monthly net household income in 2018 and 2019 and equivalized by the number of household members.

In the questionnaires of May and September, we asked all subjects that were employed or self-employed, for which support policies their employer or they themselves – if they were self-employed – applied and were not rejected. Among the self-employed, the policies with the most frequent take-up was the TOZO (26% in May; 14% in September). Tax deferrals and TOGS were the second most frequent in May (17%), followed by the NOW program (11% in May, 6% in September). Employees are targeted through the NOW program. 13% (11%) of employees indicate that their employer applied for the NOW program in May (September). A large fraction of employees indicates that they don't know whether their employer applied for NOW (27% in May, 30% in September). According to official statistics roughly 24% of employees were affected by NOW between March-May.[16] This indicates that a lot of employees are not aware of the policy take-up of their employer. We code every respondent who indicated that their employer applied and was not rejected by NOW in May or September as being affected by a support program.[17] For self-employed we consider all policies and code them as being affected by policy if they applied to any policy between March-September. We do not distinguish between take-up between March and May and June and September because the number of people affected only by the second round of policies is very small.

As additional control variable, we also use the sector an individual works in. This information is elicited in the work and schooling questionnaire in April 2020. When this information is not available, we use the answer from April 2019.

B2. Essential worker status

The Dutch government has identified a number of areas of the economy that are exempt from the restrictions on public life. Facilities in these areas remain open and parents working in these occupations are eligible for emergency daycare and after school care. A non-exhaustive list of occupations and industries includes care, youth aid and social support, including transportation and production of medicine and medical devices; teachers and school staff, required for online learning, exams and childcare; public transportation; food production and distribution, such as supermarkets, food production and food transportation, farmers, farmworkers and so forth; transportation of fuel, coal, diesel

[16] Absolute numbers can be found here: https://www.nowinzicht.nl/factsheet

[17] Rejection rates are very low see https://www.nowinzicht.nl/factsheet.

Table B.3
Characteristics of respondents in each survey wave – full sample.

	before Covid-19	march 2020	april 2020	may 2020	june 2020	september 2020	december 2020
age	44.806	45.226	45.470	45.442	45.218	45.668	45.875
	(0.215)	(0.226)	(0.226)	(0.234)	(0.225)	(0.230)	(0.237)
female	0.560	0.553	0.560	0.550	0.557	0.557	0.547
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
education: lower sec. and below	0.191	0.194	0.195	0.196	0.196	0.194	0.197
	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.007)	(0.007)
education: upper secondary	0.387	0.388	0.384	0.389	0.384	0.384	0.391
	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
education: tertiary	0.422	0.418	0.421	0.415	0.420	0.423	0.412
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
net hh income 18/19 (equiv)	2233.167	2202.449	2250.052	2216.935	2212.931	2213.192	2258.957
	(66.630)	(61.474)	(73.906)	(64.824)	(60.151)	(64.310)	(79.815)
gross income: below 2500	0.538	0.536	0.540	0.538	0.537	0.534	0.535
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.009)	(0.009)
gross income: bet. 2500 and 3500	0.224	0.225	0.220	0.227	0.224	0.229	0.225
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
gross income: above 3500	0.238	0.239	0.240	0.235	0.239	0.236	0.240
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
full time employed pre-Covid	0.426	0.426	0.422	0.420	0.424	0.424	0.430
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
part time employed pre-Covid	0.221	0.217	0.220	0.216	0.214	0.216	0.213
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
self-employed pre-Covid	0.076	0.076	0.074	0.074	0.073	0.075	0.072
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
has partner	0.693	0.694	0.696	0.699	0.696	0.694	0.700
	(0.007)	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.008)
married	0.487	0.491	0.496	0.493	0.493	0.492	0.497
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
no. children below 12	0.363	0.359	0.341	0.337	0.341	0.344	0.332
	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)
frac. work doable from home	0.427	0.423	0.423	0.429	0.428	0.428	0.426
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
essential worker	0.354	0.351	0.398	0.364	0.356	0.356	0.358
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)
affected by policy: yes	0.212	0.211	0.208	0.210	0.210	0.201	0.205
	(0.008)	(0.009)	(0.009)	(0.008)	(0.009)	(0.008)	(0.009)
affected by policy: no	0.423	0.432	0.430	0.439	0.433	0.441	0.438
	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.011)
affected by policy: don't know	0.365	0.357	0.361	0.350	0.357	0.359	0.357
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
N	4283	3850	3844	3631	3895	3641	3494

Notes: Sample: $18 \leq$ age ≤ 66. Not all variables are non-missing for each observation.

and so forth; transportation of waste and garbage; daycare; media and communications; emergency services such as fire department, ambulance, regional medical organizations; necessary administrative services on the provincial and municipality level. In addition, about 100 companies have been identified as necessary to sustain public life, operating in sectors such as gas and fuel production, distribution and transportation, communication and online services, water supply, securities trading, infrastructure, etc.

We asked the respondents directly for their essential worker status in April, but also obtain an indirect measure in March from a question about compliance to a potential curfew. The answering options were "yes", "no" or "I work in a critical profession". Whenever available we make use of the direct measure. Overall, 35% of individuals indicate that they work in an essential occupation (Table B.1). The level and the distribution over sectors lines up well with estimates based on the 2019 Labor force survey (LFS) of Statistics Netherlands.[18] In the fourth quarter of 2019, about 34% of respondents worked in an occupation later to be declared essential.

[18] For details see https://www.cbs.nl/nl-nl/faq/corona/economie/hoeveel-mensen-werken-er-in-cruciale-beroepen-.

B3. Ability to work from home

In May 2020, we ask individuals "What percentage of your normal work prior to the coronavirus outbreak can you do while working from home?". Subjects could answer a number between 0 and 100. In December, we repeated this question about their current job by asking "What percentage of your normal work can you do with working from home?". We recode this measure to range from 0 to 1, instead. Table B.2 displays number of observations, mean, standard deviation, as well as quantiles of the responses. Comparing the distribution of the measures of May and of December does not reveal large differences. 2177 subjects answered the question in May and December. For those subjects, we can directly compare the answers, to investigate the stability of the measure. The measure may vary because (1) individuals change jobs or tasks at jobs or (2) measurement error. The correlation between the measure in May and the measure in December is 0.82. That is, the measure is fairly stable. It is with 0.63 lower for those individuals that changed employment status at some point between May and December (N=215). The average difference between May and September is 0.01 and approximately half of subjects do not change their answer at all. This stability in the measure indicates that measurement error is not substantial even though the question is asked retrospectively in May.

Given the high stability of the measure and the low labor market turnover in our sample, we use the mean between the answers in May

Table B.4
Characteristics of respondents in each survey wave – working sample.

	before Covid-19	march 2020	april 2020	may 2020	june 2020	september 2020	december 2020
age	44.238	44.579	44.847	44.941	45.041	45.240	45.365
	(0.227)	(0.238)	(0.239)	(0.252)	(0.243)	(0.249)	(0.254)
female	0.524	0.518	0.522	0.519	0.519	0.518	0.505
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
education: lower sec. and below	0.135	0.137	0.137	0.138	0.133	0.136	0.137
	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
education: upper secondary	0.372	0.373	0.370	0.376	0.376	0.369	0.381
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
education: tertiary	0.492	0.489	0.493	0.486	0.491	0.496	0.481
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
net hh income 18/19 (equiv)	2391.263	2334.973	2411.652	2353.283	2359.641	2359.043	2432.614
	(67.975)	(46.616)	(75.945)	(51.495)	(48.508)	(51.150)	(85.101)
gross income: below 2500	0.397	0.393	0.397	0.392	0.386	0.387	0.386
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
gross income: bet. 2500 and 3500	0.282	0.284	0.277	0.287	0.284	0.290	0.284
	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.010)	(0.010)
gross income: above 3500	0.321	0.323	0.326	0.320	0.330	0.324	0.330
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
full time employed pre-Covid	0.616	0.618	0.615	0.618	0.622	0.618	0.629
	(0.009)	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)
part time employed pre-Covid	0.279	0.276	0.282	0.280	0.277	0.277	0.271
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
self-employed pre-Covid	0.105	0.105	0.103	0.103	0.102	0.105	0.100
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
has partner	0.713	0.714	0.719	0.724	0.718	0.714	0.723
	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
married	0.504	0.505	0.515	0.515	0.519	0.508	0.516
	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
no. children below 12	0.425	0.419	0.406	0.405	0.404	0.407	0.396
	(0.015)	(0.016)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)
frac. work doable from home	0.440	0.437	0.435	0.440	0.440	0.439	0.437
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)
essential worker	0.353	0.349	0.397	0.371	0.363	0.365	0.370
	(0.009)	(0.009)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
affected by policy: yes	0.216	0.216	0.212	0.211	0.211	0.203	0.207
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
affected by policy: no	0.437	0.445	0.444	0.461	0.453	0.461	0.456
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
affected by policy: don't know	0.347	0.339	0.345	0.328	0.335	0.336	0.337
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)
N	2962	2656	2634	2375	2518	2384	2298

Notes: Sample: $18 \leq$ age ≤ 66; working hours of at least 10 h in early March. Not all variables are non-missing for each observation.

and in December in our analysis to measure the work from home capability.

B4. Sample attrition

Tables B.3 displays summary statistics of respondents in all waves. Table B.4 shows the same measures for our main sample, i.e. all individuals working at least 10 h in the pre-pandemic period.

Except the increasing age of our sample, the only variable with a significant difference over time is essential worker status. We elicit essential worker status twice and measure a slightly higher share of essential workers in the April wave than in the March wave. Since the question in April is more precisely asked, we take the April measure as default and make use of the March measure whenever the former is missing. This leads to the combined measure being 4–5 % higher in April than in the other waves which doesn't seem to influence our main results.

Altogether, the characteristics of respondents are very stable over the waves which suggests that sample attrition does not introduce a bias in any direction.

Appendix C. Aggregate Trends

C1. Labor force and unemployment over time

The first row of Table C.1 shows the dynamics of the labor force for all respondents between the ages of 18 and 66. The share of respondents that are out of the labor force, i.e., neither working nor unemployed, but e.g., in education, retired or a home maker, increases from 24.4% before the onset of the crisis to 26.2% in May. Thereafter, it remains roughly at this level until December. Next, we focus on those individuals in the labor force and look at the unemployment rate. The second row of Table C.1 reveals that before the Covid-19 crisis, we estimate the unemployment rate to be 4.5%. Until May, it gradually rises by 1.1 percentage points and decreases slightly thereafter.

We next compare these trends to official data of Statistics Netherlands (CBS)[19]. We focus on the group of individuals aged 25–44 years since official records are not available specifically for the age range used in our analysis. Table C.2 reports the rates of unemployment and non-employment in our sample and in the official records. The trajectory are overall very similar. Until April, the rate of non-employed individuals increases by 0.8 percentage points in our sample and by 0.5 in official data. Until December, it falls even slightly below the pre-pandemic level. The level of the unemployment rate is about 1 percentage point larger in our sample compared to official records. The maximal raise in the unemployment rate and the small increase until December (0.3 and 0.2 percentage points) are fairly similar, but the timing of this pattern is different: In official data, the increase starts only in June while we measure increasing unemployment in our sample already in the months before.

[19] See https://opendata.cbs.nl/statline/#/CBS/en/dataset/80590ENG/table?ts=1620213584059.

Table C.1
Labor force status and working hours over time.

	before Covid-19	Mar	Apr	May	Jun	Sep	Dec
out of laborforce (perc.)	24.4	24.7	25.1	26.2	25.8	26.2	26.9
	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)
N	4285	3866	3863	3645	3910	3656	3509
unemployed (perc.)	4.5	4.9	5.5	5.6	5.1	5.6	5.2
	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)
N	3241	2912	2892	2689	2902	2698	2566

Notes: Source LISS. All statistics are on respondents between ages 18 and 66. For the unemployment rate, only individuals in the labor force are considered.

Table C.2
Labor force status and working hours over time (age 25–44).

	before Covid-19	Mar	Apr	May	Jun	Sep	Dec
out of laborforce (perc.)	11.1	11.6	11.9	11.7	11.6	10.6	10.3
	(0.8)	(0.9)	(0.9)	(0.9)	(0.9)	(0.9)	(0.9)
N	1560	1384	1341	1251	1372	1261	1180
unemployed (perc.)	3.6	4.3	4.5	4.8	3.9	4.0	4.0
	(0.5)	(0.6)	(0.6)	(0.6)	(0.6)	(0.6)	(0.6)
N	1387	1223	1182	1105	1213	1127	1059
out of laborf CBS	11.6	11.6	12.1	12.0	11.9	11.4	11.2
unemployed CBS	3.0	3.0	3.1	3.0	3.5	3.5	3.2

Notes: Source LISS. The last two rows report the numbers based on official records by CBS (Statistics Netherlands). All statistics are on respondents between ages 25 and 44. For the unemployment rate, only individuals in the labor force are considered.

Table C.3
Pre-Covid working hours based on Covid survey and time use survey.

	N	mean	std. dev.	min	$q_{0.25}$	$q_{0.5}$	$q_{0.75}$	max
hours early March 2020 (retrospective)	3112	33.23	12.51	0	25	36	40	80
hours November 2019 (time use survey)	1827	34.34	13.58	0	28	36	40	80
dev. in measures	1827	0.19	12.68	−60	0	0	4	63
abs. dev. in measures	1827	6.96	10.60	0	0	3	8	63

Notes: First row displays the distribution of working hours in early March 2020 while the second row shows the respective distribution for the measure based on the time use survey in November 2019. Third row displays the distribution of the intra-subject differences between November 2019 and March/April 2020. The fourth row displays the distribution of the absolute value of deviations.

The deviation could be partly caused by the fact that we didn't ask for employment status explicitely in March and April, but infer those from reported working hours and qualitative follow-up questions.

The official data is also available for a larger sample of individuals between 15 and 75 years. For this sample, the observed differences to our sample are similar. We, however, observe a higher level of non-employment and an increase of this rate over time. This is likely associated with older individuals having a higher response rate. Overall, the comparison in this section reveals that the most important changes over time visible in official records are replicated in our sample. The observed differences are unlikely to bias the result of our main analyses which is based on unconditional working hours.

C2. Robustness for aggregate trends

Our main baseline measure of working hours before the onset of the pandemic are the working hours of early March 2020. Those are asked retrospectively in late March and April. Conversely, for the working hour measures in all other periods, we ask for the working hours in the last seven days. A potential concern is that observed changes in labor supply might be driven by the different ways working hours are elicited. An alternative baseline measure is based on the time use and consumption survey that was in the field in November 2019. As participants are in this study also asked for their working hours in the last week, the elicitation method is closer to the one for our observations from March on. On the other hand, this data was elicited longer before the pandemic and the joint sample is substantially lower.

Table C.3 compares the distributions of the two measures. Based on the time use survey, mean total working hours are about one hour larger. The third row reveals that mean deviation on the individual level is below 0.2 which shows that the mean of the two measures are very similar. The absolute deviation is 7 h on average with a median of 3 h. The correlation between the measures is 0.51 which indicates that none of the samples seem to be strongly biased in any direction. Because of the larger sample size, we make use of the February data in the main body of the paper and use the time use data for robustness analyses.

Table C.4 replicates Table 1 for a different sample which includes all individuals that work at least 10 h in any of the seven periods. Importantly, we include individuals in this sample that were not working shortly before Covid-19 hit the economy, but do so afterwards. We hence avoid a mechanical drop in average unconditional working hours.

As expected, unconditional working hours are smaller for this sample. Furthermore, reductions in aggregate working hours are smaller which implies that Table 1 overestimates those, especially in later months. For our analyses, we nevertheless prefer the restriction on individuals working before the pandemic for two reasons: First, it allows to look at relative changes in working hours. Second, we only have complete information on essential worker status and ability to work from home for these individuals.

Table C.4
Working hours over time for subjects working at least 10 h in any period.

	before Covid-19	Mar	Apr	May	Jun	Sep	Dec
working hours	32.2	28.2	27.7	26.3	27.1	27.4	29.0
	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
N	3182	2857	2832	2658	2869	2693	2580
hours worked from home	3.8	14.0	14.6	12.2	10.8	8.7	12.0
	(0.2)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)	(0.3)
N	3182	2857	2832	2658	2869	2693	2580
share of hours worked from home	0.11	0.49	0.51	0.45	0.38	0.31	0.39
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	2962	2437	2408	2106	2317	2127	2052

Notes: Source LISS. Household income in thousands. All statistics are on respondents between ages 18 and 66 who worked for at least 10 h in at least one of the 7 periods.

Table C.5
Labor force status and working hours over time (weighted).

	before Covid-19	Mar	Apr	May	Jun	Sep	Dec
out of laborforce (perc.)	23.0	23.0	23.2	24.3	24.1	24.0	24.3
	(0.6)	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)	(0.7)
N	4285	3866	3851	3645	3910	3656	3509
unemployed (perc.)	4.3	4.8	5.4	5.4	5.1	5.5	4.9
	(0.4)	(0.4)	(0.4)	(0.5)	(0.4)	(0.5)	(0.4)
N	3241	2912	2883	2689	2902	2698	2566
working hours	35.0	30.8	30.0	27.1	28.2	28.1	29.8
	(0.3)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)	(0.4)
N	2962	2656	2634	2375	2518	2384	2298
hours worked from home	4.1	15.4	15.9	12.4	11.4	9.0	12.4
	(0.2)	(0.4)	(0.4)	(0.3)	(0.3)	(0.3)	(0.4)
N	2962	2656	2634	2375	2518	2384	2298
share of hours worked from home	0.11	0.49	0.52	0.45	0.39	0.31	0.40
	(0.00)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
N	2962	2437	2408	2106	2317	2127	2052

Notes: Source LISS. All statistics are on respondents between ages 18 and 66. The sample for unemployment includes all individuals in the labor force. The sample for hours include individuals who worked for at least 10 h in any one of the 5 periods. Observations are weighted based on age, sex, and marital status.

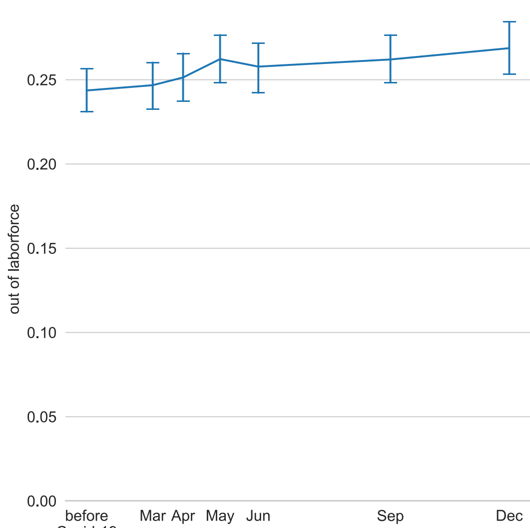


Fig. C.1. Non-participation rate. The figure shows the rate of respondents in our sample over that are neither employed nore self-employed over time. Vertical bars depict 95 %-confidence intervals. Sample: Age ≤ 65.

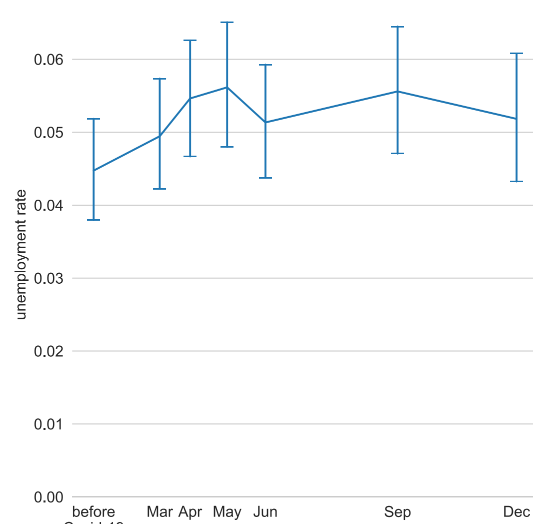


Fig. C.2. Unemployment rate. The figure shows the unemployment rate in our sample over time. Vertical bars depict 95 %-confidence intervals. Sample: 18 ≤ age ≤ 66; being employed, self-employed or unemployed in the respective month.

Table C.5 shows aggregate trends making use of sample weights. The weights are based on age, sex, and marital status of the respondents.

C3. Figures for trends over time

This subsection presents visualizations of the trajectories of labor force participation, unemployment, and total working hours (Figs. C.1, C.2, C.3).

C4. Working hours reductions and expected job loss

Working less while still earning the same might be for many individuals not a bad thing per se. However, they are likely a good proxy of who will loose their job in case the pandemic continues and economic support measures run out. Even if people who reduce working

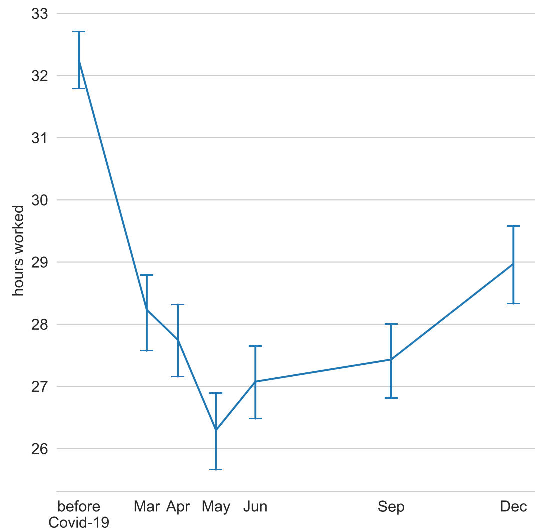


Fig. C.3. Working hours. *Notes:* The figure shows total hours worked over time. Vertical bars depict 95 %-confidence intervals. Sample: $18 \leq$ age ≤ 66; working hours of at least 10 h in at least one period.

Table C.6
Working hours reductions in March and job loss expectations.

	concerned about job	expected job loss prob.	
	(1)	(2)	(3)
change hours March	−0.013***	−0.123***	−0.095***
	(0.002)	(0.030)	(0.026)
female	−0.039	−1.165**	−0.913
	(0.044)	(0.581)	(0.556)
N	2485	2487	2470
R^2	0.128	0.033	0.027
mean dependent variable	0.034	4.464	4.304
Subset: didn't loose job	No	No	Yes
Demographic controls	Yes	Yes	Yes

Notes: Source LISS. Job concerns are measued by a 5-point Likert scale and standardized. Sample: $18 \leq$ age ≤ 66; working hours of at least 10 h in early March. For the first three columns the sample is additionally restricted to individuals working pre-Covid. $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

hours are going to keep their job later, they might face increased mental stress with respect to job security. Table C.6 shows that a reduction in working hours in March by 10 hours is associated with a 1.2 higher expected probability to loose one's job within the next two months (column (2)). This relation is not mainly driven by individuals that lost their job already (column (3)). Furthermore, it relates to an increase of self-reported job worries by 0.12 std (column (1)).

Appendix D. Predictors of working hours and household income

D1. Working hours changes by characteristics

The top row of Fig. D.1 shows total working hours by the degree of telecommutability in three categories: For the subset of non-essential workers (Fig. D.1a), roughly 3 in 10 individuals can work up to 10 % of their work from home and the same share can do so for more than 90 % of their work. This leaves 40 % of non-essential workers in the middle category. For workers who are not classified as essential, the relevance of telecommutability during the first lockdown is enormous. The fifth of the workforce that is not classified as essential worker and has very little possibility to work from home lost one third of pre-pandemic working hours, compared to 11 and 5 percentage point for intermediate and high degrees of telecommutability. These gaps have narrowed considerably to 10 percentage points or less by June and are slightly reversed in September. Until December, working hours for individuals with high or medium capability to work from home go up again, but stagnate for low telecommutability jobs.

In stark contrast to this, the ability to work from home does not have salient effects on the overall quantity of work for essential workers. Fig. D.1b shows that initially, reductions are only slightly stronger for workers without the ability to work from home. Starting from May, there is an additional 15 percentage point decrease for the group of essential workers with intermediate degrees of telecommutability. The relation between telecommutability and hours changes is generally not monotone for essential workers, whereas it is for non-essential workers.

Fig. D.1 c suggests that substituting workplace hours by home office hours is driving many of these patterns. For non-essential workers with more than 90% capability to work from home, home office hours are up by more than 20 h in March and April. For subjects in jobs with medium degrees of telecommutability, hours worked from home increase by more than 15 h during the first months of the pandemic. As restrictions are gradually lifted, home office hours decrease again in these two groups, both in terms of absolute numbers and the share of total working hours. In December, home office hours increase strongly again although not quite to the levels during the first lockdown. Conversely, in jobs in which almost all work has to be done at the workplace, the change in home office is very close to zero over the full observed period. for essential workers (Fig. D.1d), changes in hours worked from home are very similar to non-essential workers, for a given level of telecommutability.

Figure D.2 displays absolute changes in working hours for socioeconomic groups. Especially for the income groups, baseline working hours differ strongly between the groups. Therefore, absolute changes are harder to interpret as relative changes which we use in the main part of the paper.

Fig. D.3 show changes in workings hours over time by long-run household income. Fig. D.4 does so for the employed and self-employed.

Fig. D.5 shows that those self-employed that applied for government support decreased their working hours substantially in March/April. This is reassuring, as TOGS and TOZO – while not explicitly restricting working hours – targeted those who were directly affected by the social distancing regulations and those whose income fell below the social minimum. Employees affected by a policy reduced their working hours on average much less than the self-employed, however, they still reduced working hours quite substantially by more than 20 %. Further, they weakly increase their working hours between May and December.

While these results cannot tell us anything about the counterfactual scenario, they indicate that on average policies did not overcompensate the productivity loss of firms. Even though there was no formal requirement of decreasing working hours under the NOW policy, workers still worked on average substantially less hours during the policy receipt as right before the pandemic.

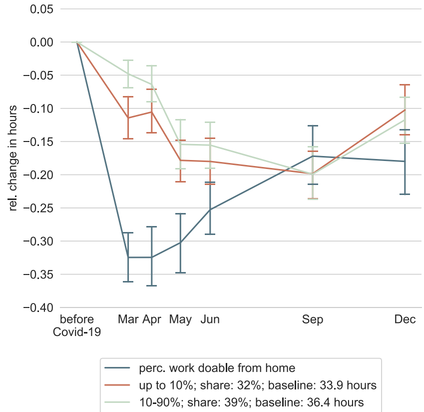
D2. Predictors of changes in working hours

A potential issue with our data is that pre-pandemic working hours are asked retrospectively for a few weeks earlier while working hours in all other periods are asked for the last week. Table D.1 shows robustness analyses for the regressions in Table 3. In the first three columns all individuals are excluded who report that they took a day off out of turn, e.g. because of official holidays, vacation, or being sick. March and June observations are dropped since we don't have this information for these months. In the last three columns, pre-pandemic working hours are based on the time use survey conducted in November 2020 that also asks for working hours during the last seven days (see Section C.2). Standard errors are larger due to the lower sample size, but observed patterns are very similar to Table 3 indicating that the different elicitation method does not drive our results.

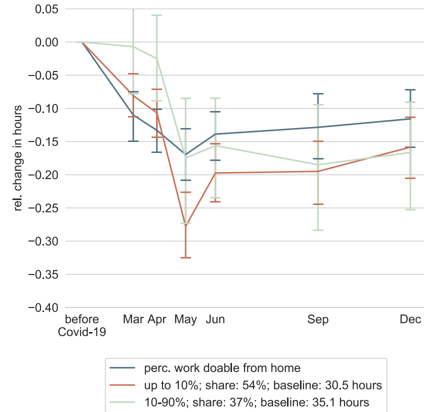
Table D.1
Hours worked by individual and job characteristics (Robustness).

	change total working hours					
	subset: no day taken off		baseline: time use survey			
	(1)	(2)	(3)	(4)	(5)	(6)
march/april × education: upper sec.	0.06**	0.03	0.02	0.03	0.01	0.00
	(0.02)	(0.02)	(0.02)	(0.05)	(0.05)	(0.05)
may × education: upper sec.	0.03	0.01	0.00	−0.04	−0.05	−0.06
	(0.05)	(0.05)	(0.05)	(0.06)	(0.05)	(0.06)
june × education: upper sec.				−0.06	−0.06	−0.07
				(0.06)	(0.06)	(0.07)
september × education: upper sec.	−0.01	0.00	0.01	−0.02	0.00	−0.03
	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.07)
december × education: upper sec.	0.02	0.02	0.01	0.02	0.03	−0.00
	(0.04)	(0.04)	(0.04)	(0.06)	(0.05)	(0.06)
march/april × education: tertiary	0.07***	0.01	0.00	0.06	0.00	0.00
	(0.02)	(0.02)	(0.03)	(0.05)	(0.05)	(0.06)
may × education: tertiary	−0.02	−0.07	−0.04	−0.02	−0.04	−0.06
	(0.05)	(0.05)	(0.06)	(0.06)	(0.07)	(0.07)
june × education: tertiary				−0.01	−0.01	−0.06
				(0.06)	(0.08)	(0.08)
september × education: tertiary	−0.01	0.01	0.03	0.08	0.12	0.07
	(0.04)	(0.04)	(0.04)	(0.07)	(0.09)	(0.10)
december × education: tertiary	0.05	0.04	0.03	0.07	0.08	0.03
	(0.04)	(0.04)	(0.04)	(0.06)	(0.07)	(0.07)
march/april × income bet. 2500 and 3500	0.07***	0.06***	0.04**	−0.01	−0.02	−0.04
	(0.02)	(0.02)	(0.02)	(0.04)	(0.04)	(0.04)
may × income bet. 2500 and 3500	0.01	−0.00	−0.04	0.03	0.03	0.00
	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.06)
june × income bet. 2500 and 3500				0.02	0.02	−0.00
				(0.04)	(0.05)	(0.05)
september × income bet. 2500 and 3500	0.03	0.03	0.03	−0.01	−0.00	−0.02
	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.06)
december × income bet. 2500 and 3500	0.00	−0.00	−0.03	0.00	0.00	−0.03
	(0.03)	(0.03)	(0.03)	(0.06)	(0.06)	(0.06)
march/april × income above 3500	0.09***	0.06***	0.04*	0.04	0.01	−0.01
	(0.02)	(0.02)	(0.02)	(0.06)	(0.07)	(0.07)
may × income above 3500	0.06	0.04	0.01	0.13	0.11	0.08
	(0.05)	(0.05)	(0.04)	(0.09)	(0.10)	(0.10)
june × income above 3500				0.07	0.07	0.06
				(0.09)	(0.11)	(0.11)
september × income above 3500	0.04	0.05	0.04	−0.06	−0.04	−0.06
	(0.03)	(0.03)	(0.03)	(0.10)	(0.11)	(0.12)
december × income above 3500	0.00	−0.01	−0.02	0.02	0.02	0.00
	(0.03)	(0.03)	(0.03)	(0.09)	(0.10)	(0.11)
march/april × essential worker		0.18***	0.16***		0.16***	0.13
		(0.02)	(0.03)		(0.05)	(0.09)
may × essential worker		0.14***	0.14**		0.06	−0.03
		(0.05)	(0.06)		(0.07)	(0.14)
june × essential worker					0.02	−0.06
					(0.08)	(0.16)
september × essential worker		0.01	0.02		−0.04	−0.12
		(0.03)	(0.04)		(0.09)	(0.16)
december × essential worker		0.04	0.06*		−0.07	−0.16
		(0.03)	(0.03)		(0.08)	(0.15)
march/april × frac. work doable from home		0.23***	0.22***		0.21***	0.21***
		(0.02)	(0.02)		(0.07)	(0.07)
may × frac. work doable from home		0.24***	0.17***		0.11	0.12
		(0.05)	(0.06)		(0.11)	(0.09)
june × frac. work doable from home					0.00	0.04
					(0.12)	(0.11)
september × frac. work doable from home		−0.03	−0.02		−0.09	−0.06
		(0.03)	(0.03)		(0.13)	(0.12)
december × frac. work doable from home		0.07**	0.06*		−0.04	−0.03
		(0.03)	(0.04)		(0.11)	(0.10)
march/april × essential × work doable from home		−0.15***	−0.12***		−0.18**	−0.14
		(0.03)	(0.04)		(0.08)	(0.09)
may × essential × work doable from home		−0.29***	−0.21**		−0.20**	−0.14
		(0.09)	(0.09)		(0.09)	(0.11)
june × essential × work doable from home					−0.07	−0.02
					(0.09)	(0.12)
september × essential × work doable from home		−0.07	−0.07		−0.08	−0.05
		(0.06)	(0.06)		(0.10)	(0.13)
december × essential × work doable from home		−0.09*	−0.09*		−0.02	0.05
		(0.05)	(0.05)		(0.09)	(0.12)
N	8161	8161	7872	10,529	10,529	10,356
R^2	0.054	0.082	0.101	0.009	0.011	0.016
demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
month × sector FE	No	No	Yes	No	No	Yes

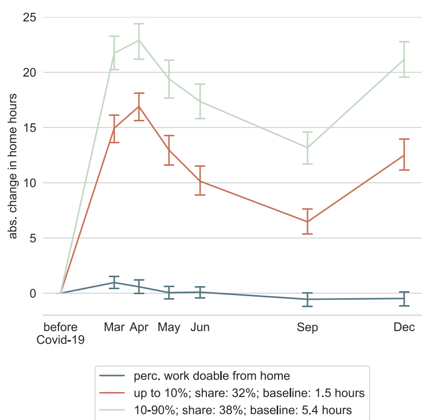
The table shows robustness analyses for the regressions in Table 3. In the first three columns all individuals are excluded who report that they took a day off because of a vacation, an official holiday, being sick, or another exceptional reason. Since we don't have this information in June, we don't make use of these observations. For the last three columns, the baseline is based on the time use and consumption survey conducted in November 2019. Further elements of the specifications include a full set of time dummies, gender, a self-employed dummy and a part-time dummy. Standard errors are clustered on the individual level. *Notes:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.



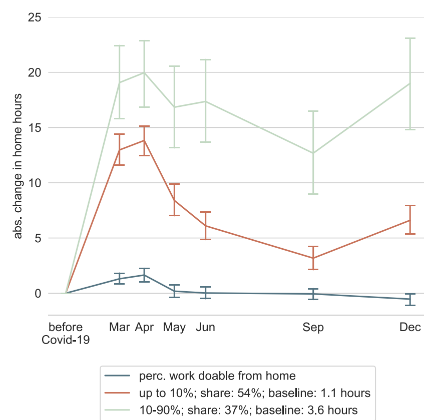
(a) Non-essential workers: Relative change in total working hours



(b) Essential workers: Relative change in total working hours

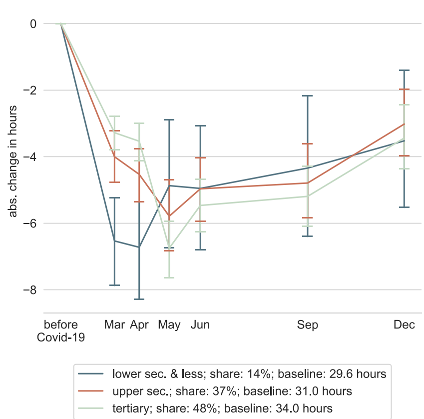


(c) Non-essential workers: Change in hours worked from home

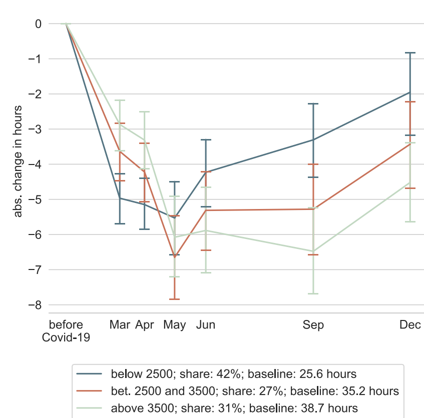


(d) Essential workers: Change in hours worked from home

Fig. D.1. Changes in total working hours and hours worked from home, by essential worker status and the percentage of work that can be done from home. *Notes:* The figure shows mean relative changes in total hours worked (top row) and mean absolute changes in hours worked from home (Panel b) over time by percentage of work that can be done from home (in three categories). The sample in the first column is restricted on non-essential workers while the second column considers only essential workers. Reference period is late February/early March. Vertical bars depict 95 %-confidence intervals. Sample: $18 \leq \text{age} \leq 66$; working hours of at least 10 h in early March. The legend displays hours and share of each group in early March.

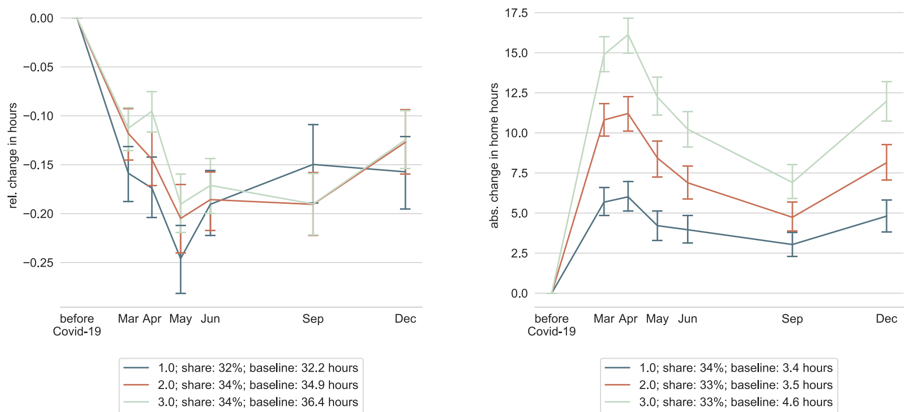


(a) Absolute change in total working hours by education



(b) Absolute change in total working hours by personal income

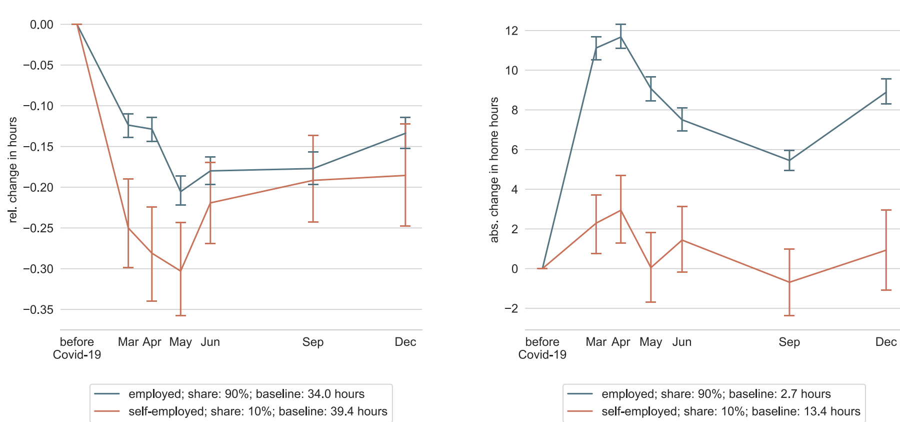
Fig. D.2. Absolute changes in total working hours, by socioeconomic status. *Notes:* The figure shows mean absolute changes in total hours worked by level of education (Panel a) and personal gross income (Panel b) over time. Reference period is late February/early March. The legend displays hours and share of each group in early March. Vertical bars depict 95 %-confidence intervals. Sample: $18 \leq \text{age} \leq 66$; working hours of at least 10 h in early March.



(a) Relative change in total working hours by household income tercile

(b) Change in hours worked from home by household income tercile

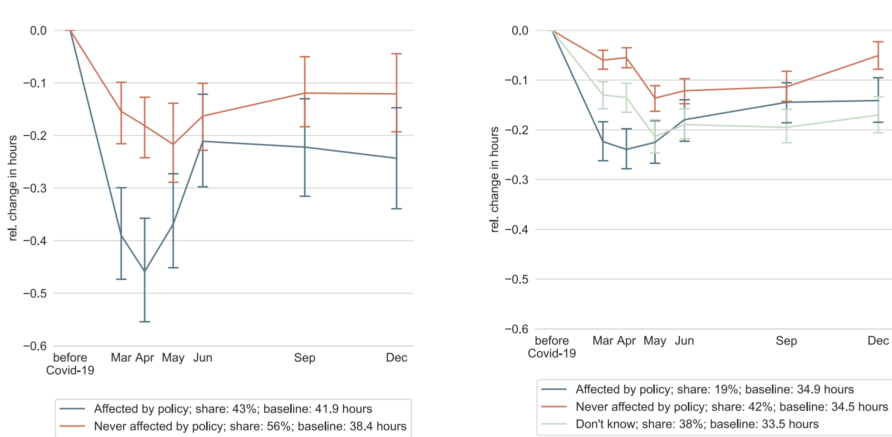
Fig. D.3. Changes in total working hours and hours worked from home, by long-run household income before Covid-19. *Notes:* The figure shows mean relative changes in total hours worked (Panel a) and mean absolute changes in hours worked from home (Panel b) over time by long-run household income tercile (equivalized). Reference period is late February/early March. The legend displays hours and share of each group in early March. Vertical bars depict 95 %-confidence intervals. Sample: 18 ≤ age ≤ 66; working hours of at least 10 h in early March.



(a) Relative hange in total working hours

(b) Change in hours worked from home

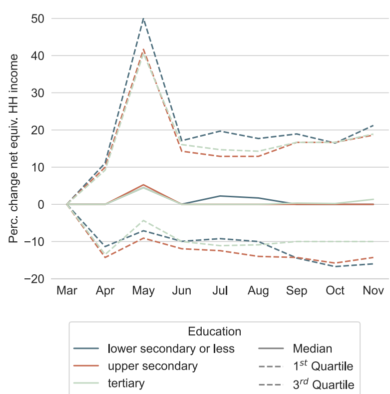
Fig. D.4. Changes in total working hours and hours worked from home, by type of employment. *Notes:* The figure shows mean relative changes in total hours worked (Panel a) and mean absolute changes in hours worked from home (Panel b) over time for self-employed and employees. Reference period is late February/early March. The legend displays hours and share of each group in early March. Vertical bars depict 95 %-confidence intervals. Sample: 18 ≤ age ≤ 66; working hours of at least 10 h in early March.



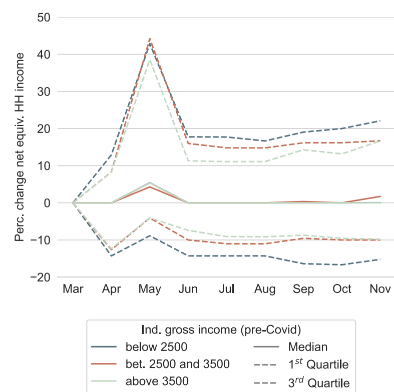
(a) Initially self-employed

(b) Initially employee

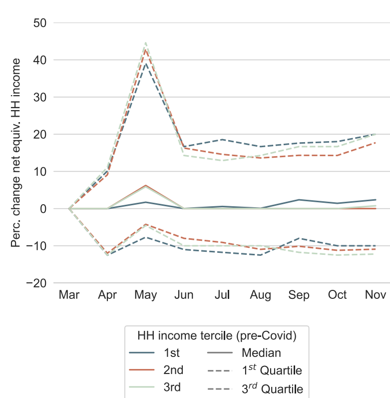
Fig. D.5. Total working hours and hours worked from home, by being affected by any support measure as elicited between March and September. *Notes:* The figure shows mean relative changes in total hours worked by being affected by any support measure sometime between March and September for initially self-employed (Panel a) and initially employed (Panel b) over time. Reference period is late February/early March. The legend displays hours and share of each group in early March. Vertical bars depict 95 %-confidence intervals. Sample: 18 ≤ age ≤ 66; working hours of at least 10 h in early March.



(a) Relative changes in net equivalized household income by education



(b) Relative changes in net equivalized household income by pre-Covid individual gross income



(c) Relative changes in net equivalized household income by pre-Covid household income

Fig. D.6. Relative changes in net equivalized household income by socioeconomic status. *Notes:* Relative change of net equivalized household income relative to the average of January and February 2020. Pre-Covid household income tercile calculated by using the terciles of the average household income of 2018 and 2019. Sample: 18 ≤ age ≤ 66, working pre-Covid, report positive household income in either January or February. In May, a vacation bonus is paid out, which is prescribed by law to be at least 8% of the yearly gross income. See https://wetten.overheid.nl/BWBR0002638/2017-01-01#HoofdstukIII for more information.

Table D.2
Hours worked by long-run household income.

	change total working hours (1)
march/april	−0.20***
	(0.03)
may	−0.19***
	(0.04)
june	−0.09**
	(0.04)
september	0.02
	(0.05)
december	−0.02
	(0.05)
march/april × working hours pre-Covid	0.00
	(0.00)
may × working hours pre-Covid	−0.00**
	(0.00)
june × working hours pre-Covid	−0.00***
	(0.00)
september × working hours pre-Covid	−0.01***
	(0.00)
december × working hours pre-Covid	−0.00***
	(0.00)
march/april × net hh income 18/19 Q2	0.03
	(0.02)
may × net hh income 18/19 Q2	0.07**
	(0.03)
june × net hh income 18/19 Q2	0.04
	(0.02)
september × net hh income 18/19 Q2	−0.01
	(0.03)
december × net hh income 18/19 Q2	0.04
	(0.03)
march/april × net hh income 18/19 Q3	0.05***
	(0.02)
may × net hh income 18/19 Q3	0.07***
	(0.03)
june × net hh income 18/19 Q3	0.03
	(0.02)
september × net hh income 18/19 Q3	−0.03
	(0.03)
december × net hh income 18/19 Q3	0.05*
	(0.03)
N	14,938
R^2	0.144

The table shows regressions of relative changes in working hours relative to pre-corona levels. Independent variables are the long-run net household income in quintiles and baseline working hours. The former is measured as the average monthly net household income in 2018 and 2019. This variable is equivalized by the number of household members. All variables are fully interacted with month-dummies. Standard errors are clustered on the individual level. *Notes:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table D.3
Hours worked and not working by individual and job characteristics.

	change total working hours			no job		
	(1)	(2)	(3)	(4)	(5)	(6)
march/april	−0.22***	−0.32***	−0.51***	0.014**	0.019***	0.011
	(0.03)	(0.03)	(0.07)	(0.006)	(0.006)	(0.010)
may	−0.28***	−0.33***	−0.47***	0.077***	0.093***	0.080**
	(0.04)	(0.04)	(0.07)	(0.019)	(0.020)	(0.037)
june	−0.35***	−0.40***	−0.38***	0.069***	0.076***	0.019
	(0.04)	(0.04)	(0.07)	(0.020)	(0.021)	(0.027)
september	−0.31***	−0.31***	−0.25**	0.108***	0.118***	0.133***
	(0.04)	(0.05)	(0.11)	(0.023)	(0.024)	(0.048)
december	−0.27***	−0.29***	−0.31***	0.101***	0.100***	0.117**
	(0.04)	(0.05)	(0.10)	(0.024)	(0.024)	(0.046)
march/april × female	−0.04***	−0.07***	−0.06***	0.000	0.001	0.001
	(0.02)	(0.02)	(0.02)	(0.004)	(0.004)	(0.004)
may × female	−0.05**	−0.05**	−0.05**	−0.013	−0.009	0.000
	(0.02)	(0.02)	(0.02)	(0.011)	(0.011)	(0.010)
june × female	−0.01	−0.02	−0.03	−0.019*	−0.016	−0.007
	(0.02)	(0.02)	(0.02)	(0.011)	(0.011)	(0.011)
september × female	−0.03	−0.03	−0.04	−0.022*	−0.019	−0.017
	(0.02)	(0.02)	(0.02)	(0.012)	(0.013)	(0.013)
december × female	−0.05**	−0.05**	−0.05*	−0.015	−0.015	−0.012
	(0.02)	(0.02)	(0.02)	(0.013)	(0.013)	(0.013)
march/april × education: upper sec.	0.06***	0.04	0.03	0.004	0.004	0.006
	(0.02)	(0.02)	(0.02)	(0.004)	(0.005)	(0.004)
may × education: upper sec.	0.03	0.01	0.01	−0.012	−0.012	0.000
	(0.03)	(0.03)	(0.03)	(0.016)	(0.016)	(0.015)
june × education: upper sec.	0.05*	0.04	0.03	−0.012	−0.012	0.004
	(0.03)	(0.03)	(0.03)	(0.016)	(0.016)	(0.015)
september × education: upper sec.	0.01	0.01	0.01	−0.021	−0.021	−0.013
	(0.04)	(0.04)	(0.04)	(0.019)	(0.019)	(0.019)
december × education: upper sec.	0.06*	0.06	0.05	−0.032	−0.032	−0.019
	(0.04)	(0.04)	(0.04)	(0.020)	(0.020)	(0.020)
march/april × education: tertiary	0.07***	0.01	0.01	0.005	0.005	0.007
	(0.02)	(0.02)	(0.03)	(0.005)	(0.006)	(0.005)
may × education: tertiary	0.00	−0.03	−0.02	−0.016	−0.018	0.002
	(0.03)	(0.03)	(0.03)	(0.017)	(0.017)	(0.017)
june × education: tertiary	0.07**	0.05	0.03	−0.018	−0.022	−0.000
	(0.03)	(0.03)	(0.03)	(0.016)	(0.017)	(0.016)
september × education: tertiary	0.04	0.06	0.06	−0.032*	−0.034*	−0.026
	(0.04)	(0.04)	(0.04)	(0.019)	(0.020)	(0.020)
december × education: tertiary	0.08**	0.06*	0.05	−0.030	−0.033	−0.018
	(0.04)	(0.04)	(0.04)	(0.021)	(0.022)	(0.022)
march/april × income bet. 2500 and 3500	0.07***	0.05***	0.04**	−0.008*	−0.008*	−0.005
	(0.02)	(0.02)	(0.02)	(0.005)	(0.004)	(0.004)
may × income bet. 2500 and 3500	0.05*	0.04	0.01	−0.032***	−0.032***	−0.017*
	(0.02)	(0.02)	(0.02)	(0.011)	(0.011)	(0.010)
june × income bet. 2500 and 3500	0.06**	0.05**	0.04	−0.013	−0.013	−0.001
	(0.02)	(0.02)	(0.02)	(0.011)	(0.011)	(0.011)
september × income bet. 2500 and 3500	0.04*	0.05*	0.03	−0.030**	−0.029**	−0.015
	(0.03)	(0.03)	(0.03)	(0.012)	(0.012)	(0.012)
december × income bet. 2500 and 3500	0.06**	0.05**	0.03	−0.028**	−0.029**	−0.016
	(0.03)	(0.03)	(0.03)	(0.014)	(0.014)	(0.014)
march/april × income above 3500	0.11***	0.07***	0.06***	−0.010**	−0.010**	−0.007
	(0.02)	(0.02)	(0.02)	(0.005)	(0.005)	(0.004)
may × income above 3500	0.09***	0.07**	0.05*	−0.022*	−0.024*	−0.010
	(0.03)	(0.03)	(0.03)	(0.012)	(0.012)	(0.012)
june × income above 3500	0.04	0.03	0.03	−0.008	−0.011	−0.000
	(0.03)	(0.03)	(0.03)	(0.012)	(0.012)	(0.012)
september × income above 3500	0.01	0.02	0.00	−0.006	−0.006	0.010
	(0.03)	(0.03)	(0.03)	(0.014)	(0.014)	(0.014)
december × income above 3500	0.04	0.03	0.02	−0.021	−0.023	−0.011
	(0.03)	(0.03)	(0.03)	(0.015)	(0.015)	(0.015)
march/april × part time pre-Covid	0.02	0.03	0.03	0.006	0.007	0.007
	(0.02)	(0.02)	(0.02)	(0.005)	(0.005)	(0.005)
may × part time pre-Covid	0.04	0.04	0.03	0.042***	0.046***	0.052***
	(0.03)	(0.03)	(0.03)	(0.014)	(0.015)	(0.014)
june × part time pre-Covid	0.05*	0.05*	0.05*	0.039***	0.042***	0.041***
	(0.03)	(0.03)	(0.03)	(0.014)	(0.014)	(0.014)
september × part time pre-Covid	0.07**	0.06**	0.07**	0.058***	0.061***	0.063***
	(0.03)	(0.03)	(0.03)	(0.016)	(0.016)	(0.017)
december × part time pre-Covid	0.10***	0.11***	0.10***	0.048***	0.049***	0.054***
	(0.03)	(0.03)	(0.04)	(0.017)	(0.017)	(0.017)

(*continued on next page*)

Table D.3 (*continued*)

	change total working hours			no job		
	(1)	(2)	(3)	(4)	(5)	(6)
march/april × self-employed pre-Covid	−0.13***	−0.11***	−0.11***	−0.008***	−0.009***	−0.011***
	(0.03)	(0.02)	(0.03)	(0.002)	(0.003)	(0.003)
may × self-employed pre-Covid	−0.09**	−0.08**	−0.10***	0.010	0.003	0.011
	(0.03)	(0.03)	(0.03)	(0.013)	(0.014)	(0.014)
june × self-employed pre-Covid	−0.03	−0.03	−0.02	0.001	−0.003	−0.000
	(0.03)	(0.03)	(0.03)	(0.012)	(0.012)	(0.013)
september × self-employed pre-Covid	−0.00	−0.00	−0.00	0.006	0.002	−0.001
	(0.03)	(0.03)	(0.04)	(0.015)	(0.015)	(0.016)
december × self-employed pre-Covid	−0.03	−0.03	−0.04	0.038*	0.037*	0.041*
	(0.03)	(0.03)	(0.03)	(0.020)	(0.020)	(0.021)
march/april × age: between 36 and 55	0.01	0.02	0.01	−0.009**	−0.009**	−0.009**
	(0.02)	(0.02)	(0.02)	(0.004)	(0.004)	(0.004)
may × age: between 36 and 55	0.06**	0.07***	0.06**	−0.031***	−0.031***	−0.028***
	(0.02)	(0.02)	(0.03)	(0.011)	(0.011)	(0.010)
june × age: between 36 and 55	0.12***	0.12***	0.12***	−0.033***	−0.033***	−0.030***
	(0.02)	(0.02)	(0.02)	(0.010)	(0.010)	(0.010)
september × age: between 36 and 55	0.14***	0.14***	0.13***	−0.057***	−0.057***	−0.051***
	(0.03)	(0.03)	(0.03)	(0.012)	(0.012)	(0.013)
december × age: between 36 and 55	0.09***	0.09***	0.07***	−0.038***	−0.038***	−0.033***
	(0.03)	(0.03)	(0.03)	(0.012)	(0.012)	(0.012)
march/april × age: above 55	−0.04*	−0.03	−0.03	−0.003	−0.003	−0.002
	(0.02)	(0.02)	(0.02)	(0.005)	(0.005)	(0.006)
may × age: above 55	0.03	0.03	0.04	−0.006	−0.005	0.002
	(0.03)	(0.03)	(0.03)	(0.014)	(0.014)	(0.014)
june × age: above 55	0.10***	0.10***	0.09***	0.006	0.007	0.013
	(0.03)	(0.03)	(0.03)	(0.014)	(0.014)	(0.014)
september × age: above 55	0.06**	0.06*	0.05*	0.004	0.004	0.012
	(0.03)	(0.03)	(0.03)	(0.017)	(0.017)	(0.017)
december × age: above 55	0.00	0.00	−0.00	0.036**	0.036**	0.042**
	(0.03)	(0.03)	(0.03)	(0.018)	(0.018)	(0.018)
march/april × essential worker		0.17***	0.15***		−0.013**	−0.015**
		(0.02)	(0.03)		(0.005)	(0.007)
may × essential worker		0.09***	0.08**		−0.048***	−0.031**
		(0.03)	(0.03)		(0.013)	(0.013)
june × essential worker		0.10***	0.10***		−0.027**	−0.020
		(0.03)	(0.03)		(0.012)	(0.012)
september × essential worker		0.03	0.03		−0.031**	−0.023
		(0.03)	(0.04)		(0.016)	(0.017)
december × essential worker		0.03	0.04		−0.002	−0.002
		(0.03)	(0.03)		(0.017)	(0.018)
march/april × frac. work doable from home		0.24***	0.22***		−0.004	−0.006
		(0.02)	(0.02)		(0.007)	(0.007)
may × frac. work doable from home		0.15***	0.15***		−0.008	−0.022
		(0.03)	(0.03)		(0.016)	(0.018)
june × frac. work doable from home		0.10***	0.13***		0.006	−0.014
		(0.03)	(0.03)		(0.016)	(0.018)
september × frac. work doable from home		−0.04	−0.02		−0.004	−0.015
		(0.03)	(0.03)		(0.018)	(0.019)
december × frac. work doable from home		0.07**	0.09**		0.010	−0.008
		(0.03)	(0.04)		(0.019)	(0.021)
march/april × essential × work doable from home		−0.15***	−0.12***		0.013	0.017*
		(0.03)	(0.04)		(0.008)	(0.009)
may × essential × work doable from home		−0.19***	−0.16***		0.033*	0.036*
		(0.05)	(0.05)		(0.019)	(0.019)
june × essential × work doable from home		−0.16***	−0.19***		0.006	0.015
		(0.05)	(0.05)		(0.019)	(0.019)
september × essential × work doable from home		−0.05	−0.06		0.012	0.005
		(0.06)	(0.06)		(0.026)	(0.025)
december × essential × work doable from home		−0.09*	−0.09*		−0.013	−0.010
		(0.05)	(0.05)		(0.028)	(0.028)
march/april × sector: construction			0.32***			0.009
			(0.07)			(0.012)
may × sector: construction			0.29***			0.005
			(0.08)			(0.044)
june × sector: construction			0.05			0.030
			(0.08)			(0.028)
september × sector: construction			0.03			−0.048
			(0.11)			(0.047)
december × sector: construction			0.09			−0.055
			(0.10)			(0.048)
march/april × sector: education			0.18**			0.001
			(0.07)			(0.011)

(*continued on next page*)

Table D.3 (*continued*)

	change total working hours			no job		
	(1)	(2)	(3)	(4)	(5)	(6)
may × sector: education			0.05			−0.041
			(0.08)			(0.038)
june × sector: education			0.08			0.012
			(0.08)			(0.022)
september × sector: education			−0.05			−0.024
			(0.10)			(0.046)
december × sector: education			0.01			−0.033
			(0.09)			(0.047)
march/april × sector: env., culture, recr.			0.09			0.010
			(0.08)			(0.017)
may × sector: env., culture, recr.			0.09			−0.018
			(0.08)			(0.043)
june × sector: env., culture, recr.			−0.15*			0.043
			(0.09)			(0.032)
september × sector: env., culture, recr.			−0.07			0.015
			(0.11)			(0.056)
december × sector: env., culture, recr.			−0.04			−0.048
			(0.11)			(0.050)
march/april × sector: financial & business services			0.25***			0.006
			(0.07)			(0.009)
may × sector: financial & business services			0.19**			−0.010
			(0.08)			(0.039)
june × sector: financial & business services			−0.02			0.043*
			(0.08)			(0.025)
september × sector: financial & business services			−0.06			−0.023
			(0.10)			(0.045)
december × sector: financial & business services			0.04			−0.024
			(0.09)			(0.046)
march/april × sector: healthcare & welfare			0.25***			0.010
			(0.07)			(0.010)
may × sector: healthcare & welfare			0.21***			−0.051
			(0.07)			(0.037)
june × sector: healthcare & welfare			0.02			0.008
			(0.08)			(0.021)
september × sector: healthcare & welfare			−0.03			−0.052
			(0.10)			(0.044)
december × sector: healthcare & welfare			0.02			−0.049
			(0.09)			(0.046)
march/april × sector: industry			0.25***			0.001
			(0.07)			(0.009)
may × sector: industry			0.17**			−0.026
			(0.07)			(0.038)
june × sector: industry			0.04			0.019
			(0.08)			(0.023)
september × sector: industry			−0.02			−0.056
			(0.10)			(0.044)
december × sector: industry			0.06			−0.059
			(0.09)			(0.045)
march/april × sector: other			0.25***			0.006
			(0.07)			(0.010)
may × sector: other			0.16**			−0.025
			(0.07)			(0.038)
june × sector: other			−0.00			0.033
			(0.08)			(0.024)
september × sector: other			−0.05			−0.034
			(0.10)			(0.045)
december × sector: other			0.06			−0.040
			(0.09)			(0.046)
march/april × sector: public services			0.24***			−0.002
			(0.07)			(0.009)
may × sector: public services			0.14*			−0.021
			(0.07)			(0.039)
june × sector: public services			−0.04			0.034
			(0.08)			(0.025)
september × sector: public services			−0.04			−0.045
			(0.10)			(0.045)
december × sector: public services			0.02			−0.034
			(0.09)			(0.046)
march/april × sector: retail			0.22***			0.007
			(0.07)			(0.010)

(*continued on next page*)

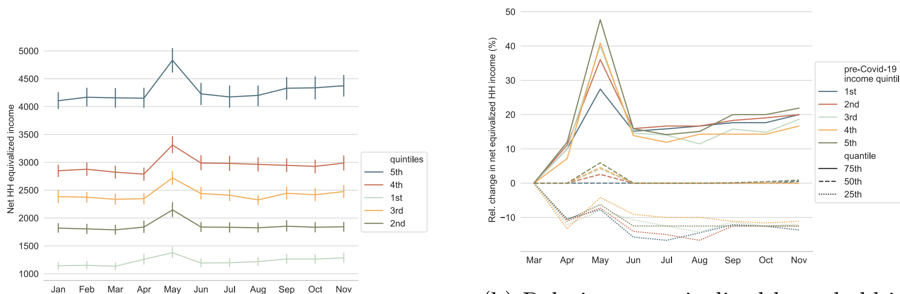
Table D.3 (*continued*)

	change total working hours			no job		
	(1)	(2)	(3)	(4)	(5)	(6)
may × sector: retail			0.18**			0.000
			(0.07)			(0.040)
june × sector: retail			0.03			0.047*
			(0.08)			(0.027)
september × sector: retail			−0.08			−0.037
			(0.10)			(0.046)
december × sector: retail			0.09			−0.043
			(0.10)			(0.046)
march/april × sector: transport, communication, & utilities			0.22***			0.000
			(0.08)			(0.009)
may × sector: transport, communication, & utilities			0.15*			−0.012
			(0.08)			(0.040)
june × sector: transport, communication, & utilities			−0.10			0.062**
			(0.08)			(0.031)
september × sector: transport, communication, & utilities			−0.09			−0.035
			(0.11)			(0.047)
december × sector: transport, communication, & utilities			0.01			−0.010
			(0.10)			(0.050)
N	15,738	15,738	15,133	15,796	15,796	15,181
R^2	0.159	0.173	0.182	0.073	0.077	0.077

Dependent variable in the first columns are unconditional working hours. This part of the table shows the full set of covariates for the regressions shown in Table 3. The dependent variable in the last three columns is a dummy variable if the individual is either out of the laborforce or unemployed. Standard errors are clustered on the individual level. The data are an unbalanced panel restricted to individuals who worked more than ten hours in early March. Reference period = Early March. *Notes:* $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

D3. Predictors of household income

Fig. D.7 and Tables D.4, D.5, D.6.



(a) Net equivalized household income by long-run income quintile pre-Covid

(b) Relative et equivalized household income by long-run income quintile pre-Covid

Fig. D.7. Evolution of net equivalized household income by pre-Covid income quintile. *Notes:* Net equivalized household income by long run income quintile. Long run income quintile calculated by using the quintiles of the average household income of 2018 and 2019. Sample: 18 ≤ age ≤ 66.

Table D.4
Net equivalized household income by characteristics.

	Jan	Feb	Mar	Apr	May	June	July	Aug	Sep	Oct	Nov
All	2395	2406	2381	2421	2792	2454	2435	2425	2489	2482	2519
Employment status pre-Covid											
employed	2727	2750	2737	2773	3261	2816	2793	2789	2833	2822	2877
self-employed	2787	2821	2597	2491	2756	2922	2857	2745	3022	2959	2973
not working	1603	1591	1586	1714	1928	1644	1653	1643	1698	1706	1716
Initial employment shock											
decreased at least 20 h	2404	2394	2159	2151	2609	2313	2265	2350	2486	2431	2511
decreased less than 20 h	2545	2585	2560	2517	2915	2641	2607	2549	2602	2582	2638
did not decrease	2363	2372	2366	2442	2828	2451	2441	2433	2490	2486	2516
Policy Take-up											
Affected by policy, March-Sept	2655	2678	2525	2498	2893	2705	2698	2699	2601	2575	2610
Affected by policy, March-May	2512	2567	2485	2380	2772	2707	2637	2653	2820	2732	2753
Affected by policy, June-Sept	2567	2564	2504	2498	3005	2563	2539	2496	2767	2773	2770
Never affect by policy	2835	2877	2862	2848	3362	2907	2895	2881	2954	2950	3009
Reason for reduction											
closure	2354	2360	2209	2161	2527	2273	2278	2297	2463	2432	2462
less business	2456	2469	2388	2383	2683	2472	2443	2460	2481	2438	2478
care	2894	3004	2853	2816	3373	3194	2986	3104	3275	3263	3280
other	2617	2670	2692	2737	3299	2764	2724	2633	2669	2644	2772
no reduction	2356	2363	2359	2428	2811	2447	2436	2425	2479	2478	2506
Income quintile pre-Covid											
1st	1143	1151	1135	1259	1381	1195	1200	1221	1269	1267	1289
2nd	1826	1813	1796	1847	2156	1841	1839	1827	1877	1859	1868
3rd	2382	2371	2332	2343	2720	2443	2411	2330	2428	2401	2458
4th	2849	2876	2823	2788	3307	2987	2978	2960	2945	2926	2985
5th	4111	4173	4162	4154	4835	4229	4177	4208	4335	4343	4380

Notes: Average monthly net equivalized household income by characteristics. Long run income quintile calculated by using the quintiles of the average household income of 2018 and 2019. Sample: 18 ≤ age ≤ 66.

Table D.5
Relative change in equivalized household income by characteristics.

month	Mar			Apr			May			June			July			Aug			Sep			Oct			Nov		
quantile	p25	p50	p75	p25	p50	p75	p25	p50	p75	p25	p50	p75	p25	p50	p75	p25	p50	p75	p25	p50	p75	p25	p50	p75	p25	p50	p75
All	0	0	0	−12	0	10	−7	2	40	−13	0	14	−14	0	14	−14	0	15	−13	0	17	−13	0	17	−13	0	20
Employment status pre-Covid																											
employed	0	0	0	−11	0	10	−4	6	46	−9	0	15	−10	0	14	−10	0	14	−11	0	17	−11	0	17	−11	1	18
self-employed	−20	0	0	−33	−7	11	−29	0	21	−25	0	22	−29	0	20	−29	0	20	−29	0	25	−31	0	25	−31	0	25
not working	0	0	0	−12	0	12	−10	0	33	−19	0	12	−20	0	12	−20	0	14	−14	0	18	−14	0	20	−14	0	20
Initial employment shock																											
decreased at least 20 h	−8	0	0	−29	0	7	−20	0	40	−20	−2	11	−20	0	12	−20	0	12	−19	0	21	−20	0	20	−20	0	24
decreased less than 20 h	0	0	0	−16	0	11	−11	4	43	−16	0	17	−18	0	17	−19	0	17	−17	0	17	−19	0	17	−17	0	20
did not decrease	0	0	0	−12	0	12	−7	4	40	−12	0	14	−12	0	14	−13	0	14	−12	0	17	−12	0	17	−12	0	19
Policy Take-up																											
Affected by policy, March-Sept	0	0	0	−16	0	7	−12	0	37	−10	0	23	−12	0	21	−11	0	18	−12	0	14	−14	0	14	−16	0	20
Affected by policy, March-May	0	0	0	−16	0	9	−12	0	29	−17	0	17	−17	0	16	−18	0	20	−22	0	20	−24	0	18	−24	0	20
Affected by policy, June-Sept	0	0	0	−11	0	2	−8	2	49	−9	0	17	−8	0	17	−9	0	17	−9	0	22	−9	0	21	−9	0	21
Never affect by policy	0	0	0	−12	0	11	−4	7	48	−10	0	16	−10	0	15	−10	0	15	−10	1	17	−10	1	17	−10	2	20
Reason for reduction																											
closure	0	0	0	−22	0	11	−17	2	46	−20	0	17	−19	0	18	−17	0	19	−17	0	24	−19	0	25	−17	1	25
less business	0	0	0	−17	0	10	−12	0	30	−17	0	14	−17	0	14	−18	0	14	−17	0	14	−21	0	14	−20	0	15
care	0	0	0	−19	0	4	−12	5	40	−18	0	13	−20	−2	12	−15	−1	12	−9	0	17	−9	0	17	−9	0	17
other	0	0	0	−11	0	12	−5	10	56	−14	0	16	−16	0	14	−18	0	14	−17	0	19	−17	0	19	−17	1	23
no reduction	0	0	0	−12	0	11	−7	4	40	−12	0	14	−12	0	14	−13	0	14	−12	0	17	−12	0	17	−12	0	19
Income quintile pre-Covid																											
1st	0	0	0	−10	0	10	−8	0	27	−16	0	15	−17	0	16	−15	0	17	−12	0	18	−13	0	18	−14	0	20
2nd	0	0	0	−11	0	11	−7	3	36	−14	0	16	−15	0	17	−17	0	17	−13	0	18	−13	0	19	−12	0	20
3rd	0	0	0	−12	0	10	−8	4	40	−10	0	15	−12	0	14	−14	0	11	−11	0	16	−12	0	15	−12	0	18
4th	0	0	0	−13	0	7	−4	5	40	−9	0	14	−10	0	11	−10	0	14	−11	0	14	−11	0	14	−11	0	17
5th	0	0	0	−11	0	12	−6	6	48	−12	0	16	−12	0	14	−12	0	15	−12	0	20	−12	0	20	−12	1	22

Notes: Quartiles of the relative changes in net equivalized household income by characteristics. Long run income quintile calculated by using the quintiles of the average household income of 2018 and 2019. Sample: $18 \leq \text{age} \leq 66$ and household income positive in January or February 2020.

Table D.6
Quantile regression: household income and pre-Covid income quintiles.

	Rel. change net equiv. HH inc. (%)		
	p25	p50	p75
Apr	−16.48***	0	21.07***
	(4.43)	(0.49)	(4.65)
May	−11.66**	11.89***	44.3***
	(4.65)	(3.37)	(6.49)
Jun	−14.93***	0	26.5***
	(4.66)	(1.01)	(3.89)
Sep	−14***	3.78	24.95***
	(4.89)	(2.52)	(4.52)
Apr × 2nd income quintile	−0.3	0	0.73
	(4.26)	(0.55)	(4.57)
Apr × 3rd income quintile	2.84	0	−0.07
	(3.56)	(0.5)	(4.77)
Apr × 4th income quintile	−0.53	0	−3.67
	(3.56)	(0.49)	(3.99)
Apr × 5th income quintile	2.32	0	0.29
	(3.77)	(0.5)	(4.1)
May × 2nd income quintile	1.24	−0.53	1.23
	(4.82)	(3.17)	(7.56)
May × 3rd income quintile	2.86	2.54	9.13
	(4.61)	(3.29)	(8.7)
May × 4th income quintile	6.89	1.87	9.13
	(4.3)	(3.02)	(6.7)
May × 5th income quintile	3.12	3.43	9.15
	(4.05)	(3.66)	(7.56)
Jun × 2nd income quintile	4.38	2.82**	0.06
	(4.78)	(1.35)	(4.21)
Jun × 3rd income quintile	3.46	0	−0.42
	(4.57)	(0.76)	(4.31)
Jun × 4th income quintile	4.36	0	−3.26
	(4.19)	(0.7)	(4.08)
Jun × 5th income quintile	−0.81	0	−2.61
	(4.85)	(0.6)	(4.06)
Sep × 2nd income quintile	−5.61	−3.92*	−4.79
	(5.99)	(2.2)	(4.85)
Sep × 3rd income quintile	−3.5	−4.65**	−5.54
	(4.96)	(1.88)	(4.82)
Sep × 4th income quintile	−6	−4.65**	−8.89**
	(4.6)	(2.01)	(3.76)
Sep × 5th income quintile	−8.29	−4.79**	−3.99
	(5.17)	(2.01)	(4.27)
Apr × work. hours (pre-Covid)	0.02	0	−0.21**
	(0.11)	(0)	(0.09)
May × work. hours (pre-Covid)	0.05	−0.21***	−0.22
	(0.11)	(0.07)	(0.2)
Jun × work. hours (pre-Covid)	0.09	0	−0.27***
	(0.09)	(0.02)	(0.08)
Sep × work. hours (pre-Covid)	0.25***	0.04	−0.06
	(0.07)	(0.05)	(0.09)
N	9030	9030	9030

Notes: Quantile regression of relative changes in net equalized household income on pre-Covid income quintiles. Standard errors clustered on the household level using wild bootstrapped procedure as proposed by Hagemann (2017) and implemented in the R package quantreg. Sample: $18 \leq$ age ≤ 66; employed or self-employed pre-Covid (early March) and working hours of at least 10 h in early March; positive household income either in January or February 2020.

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