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# The Dynamics of Remote Work: Productivity and Work-Life Balance Before, During, and After COVID-19

An Examination of Work From Home Trends and Their Impact on Working Hours and Work-Life Integration

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**Abstract**

With Work From Home (WFH) becoming more normalized since its rapid adoption during the COVID-19 pandemic, 52% of the Dutch workforce still spends some time working from home. WFH does not only influence employees way of working, but also their home lives. In this research, I examine how Dutch employees are affected by WFH between 2018-2023, specifically in combination with household and childcare responsibilities. Additionally, I make a difference between parents and non-parents and various job sectors. In order to do this, I make use of Fixed Effects regressions with panel data from the LISS Panel, which allow me to observe employees' over time and account for unobserved heterogeneity. Time specific shocks are accounted for by controlling for different stages of the COVID-19 pandemic. Although no conclusive statements can be made from the results, I did find suggestive evidence that full-timers and part-timers experience different effects from WFH. As part-timers are more often female and full-timers more often male, results can give an indication of gender differences. The presence of children often reduces employees' work time, and the division of tasks might play a role in the effects WFH has. Overall, the results indicate that while WFH has become more prevalent and that there are potential benefits, its impacts on work hours and responsibilities are complex and vary among different groups. Employers and policymakers should take a nuanced approach in crafting WFH policies, considering factors like gender, employment status (full-time vs. part-time), and parental responsibilities to effectively support their workforce.

# Contents

# 1 Introduction

The COVID-19 pandemic accelerated the switch to teleworking, a trend that still persists today. In 2023, 52% of the Dutch workforce worked at least some days from home. This gives the Netherlands the highest number of occasional teleworkers in the EU (CBS, 2024b). Work from home (WFH) not only influences the way individuals work, but also their productivity and lifestyle. Impacts include increased autonomy and flexibility, but also increased isolation and stress, and decreased contact with supervisors and coworkers (Chatterjee et al., 2022; Galanti et al., 2021; Nakrošienė et al., 2019). These impacts are expected to differ based on personal characteristics like self-discipline and time-management, but also gender (Collins et al., 2021; Tomei, 2021; Wang et al., 2021). WFH can enhance work-life balance (WLB) by making it easier to manage unpaid work alongside paid work (Vilhelmson and Thulin, 2016). The existing literature shows differential effects of teleworking on women's careers, especially highlighting the differences between theoretical benefits and practical outcomes. Although Schieman et al. (2021) did not find different effects between genders, other studies found that during COVID-19, women were relatively more likely than men to temporarily stop working (Çoban, 2022; EESC, 2021). These variations emphasize the complex relationship between WFH arrangements and the ability to combine paid and unpaid work. The mechanisms that drive these variations include gendered expectations in household labor, the unequal division of household and care responsibilities and time management in a home setting. Along with increased WFH prevalence, this can be influential on the impact of WFH on WLB. Although extensive research has been done on teleworking before and during the COVID-19 pandemic, the after effects have not yet been extensively studied. During COVID, evidence was found on possible negative effects of WFH (Adisa et al., 2022; Becker et al., 2022). Wang et al. (2021) argue that the unique context of the pandemic might change assumed theoretical relationships, and thus that the traditional way of looking at things might offer limited insights into reality. Given the mixed findings, as well as the suggested differences due to context, it is interesting to explore how WFH-effects evolve over the different COVID periods, leading to the following research question:

*"How has the shift to teleworking affected the work hours of Dutch employees, specifically in terms of reductions to part-time employment due to household and childcare responsibilities, from 2018 to 2023, and how do these changes differ between parents and non-parents, with different responsibilities, and among various job sectors"*

In this research, I rely on the definition of telework by Di Martino and Wirth (1990): "A flexible work arrangement whereby workers work in locations, remote from their central offices or production facilities, the worker has no personal contact with co-workers there, but is able to communicate with them using technology." The amount of telework is measured by taking the answer to the amount of (partial) WFH days the respondent has. In an additional analysis, I will look at the amount of hours someone works from home. Taking care of the household involves food preparation, laundry, house cleaning, odd jobs in and around the house, financial administration and grocery shopping, of which the division is captured in the Household Division Index. The Care Division Index involves the distribution of tasks related to taking care of children, such as playing with them, driving them to school or other places, discussing their problems, and going on small outings. By including age categories for children between 0-4, 5-11 and 12+, I also account for possibly unobserved care tasks for these groups.

I specifically look into how Dutch workers have developed their productivity, in terms of hours worked, through work-life balance (WLB) when increasing their work-from-home (WFH) hours. WLB plays a crucial role in this context, as it involves the ability to effectively manage and integrate paid work with unpaid household tasks and childcare responsibilities. Factors such as job autonomy, flexibility in scheduling, support from employers, the division of household labor, and the age and needs of children are all integral to achieving a balanced WLB. By understanding how these factors interact, I aim to shed light on the ways in which WFH can enhance productivity without compromising personal well-being. I examine the progression of work-from-home (WFH) practices and their impact on productivity and work-life balance (WLB) across four distinct periods: before COVID-19 (2018-2019), during the COVID-years 2020 and 2021, and after COVID-19 (2022-2023). By comparing these periods, I provide comprehensive insights into the evolution of the effects of WFH over time, specifically around the COVID pandemic. I expect each period to come with different challenges and benefits, causing varying effects to occur. Further, I explore how WFH habits have changed over time and impacted productivity when the specific context of COVID was removed.

The sample exists of employees aged 15-75, excluding individuals with multiple jobs, unemployed individuals, students, retirees, and those performing unpaid work or on parental leave. The research is grounded in the Job Characteristics Model (JCM), Job Demands-Resources Model (JD-R), Social Exchange Theory (SET), and Conservation of Resources Theory (COR). These theories help to explain the relationship between productivity and WLB under teleworking.

Analysis is done by using a Fixed Effects model with panel data obtained from the LISS Panel. Fixed effects analysis allows me to account for unobserved heterogeneity that is constant over time. Because COVID is a time-specific shock, I also add time periods to the model, to account for period differences.

Results to the analysis are not conclusive, but point to different effects for full-time and part-time employees. However, in general, children seem to decrease parents' work hours. Finally, division of tasks seems to play a role in how WFH affects work time.

As teleworking becomes increasingly integrated as a standard mode of operation, studying this question is both relevant and intriguing. Since this study looks at two years before, two during and two after COVID, it makes the results more robust. Teleworking might increase productivity through more working hours, which can help with labor market tightness (SER, 2022). The study will examine the variations in teleworking's impact across different groups, including parents vs. non-parents, different responsibilities and various sectors. Understanding these dynamics is vital for developing policies that support a balanced work-life integration and work arrangements that accommodate diverse employee needs and promote equitable work environments. This research not only contributes to academic and practical understanding of the post-pandemic work environment but also supports the development of informed strategies that can enhance both individual well-being and organizational performance.

This research will be structured in the following way. Firstly, I discuss relevant literature to outline the framework of the analyses. Both different theories and influential factors are discussed. Next, I formulate a theoretical model and hypotheses. I then follow up by discussing the research design, as well as the data used. In this part, I also discuss how data was cleaned, as well as some interesting summary statistics. Next, I discuss the results following from the analyses. Finally, I conclude the research by answering my research question, discussing limitations and suggesting improvements and interesting future research.

## 2 Literature review

In this section, I discuss existing research on Work From Home (WFH) and its impact on productivity. I examine how WFH has had different effects before and during COVID-19. My focus is on the potential for WFH to improve productivity, through its own mechanisms and work-life balance (WLB), but specifically through increasing work hours.

### 2.1 Work From Home and Productivity

Existing research uses various terminologies for WFH. It is often used interchangeably with teleworking and remote work. Di Martino and Wirth (1990) define remote working as "a flexible work arrangement whereby workers work in locations, remote from their central offices or production facilities, the worker has no personal contact with co-workers there, but is able to communicate with them using technology".

Productivity can be measured in many different ways. In the Job Characteristics Model (JCM), productivity is based on both qualitative and quantitative outcomes, and is dependent on job characteristics (Hackman and Oldham, 1976). While quantitative outcomes are easier to measure, the quality of the work is also important for the firm's productivity and success. Other theories linked to motivation and productivity in the context of working from home are the Job Demands-Resources Model and the Social Exchange Theory. Finally, the Conservation of Resources theory explains how these resources are used to maintain productivity as well as general satisfaction and balance. Besides these theories, I involve real world influences and factors to shape my expectations of the outcomes to the questions I pose in this research.

#### 2.1.1 Job Characteristics Model

According to the Job Characteristics Model (JCM), there are five job characteristics that are important for productivity and worker motivation: skill variety, task identity, task significance, autonomy and feedback. The JCM states that workers perform well if they know how they performed, believe that they are responsible for their work, and when the work is meaningful to them. These psychological states, influenced by the previously mentioned job dimensions, lead to personal and work outcomes that manifest as various forms of productivity. Figure 1 organizes these cause and effect relationships (Hackman and Oldham, 1976). The JCM characteristics influence productivity both in traditional office settings and in WFH scenarios. They are crucial in determining how WFH can optimize worker productivity.

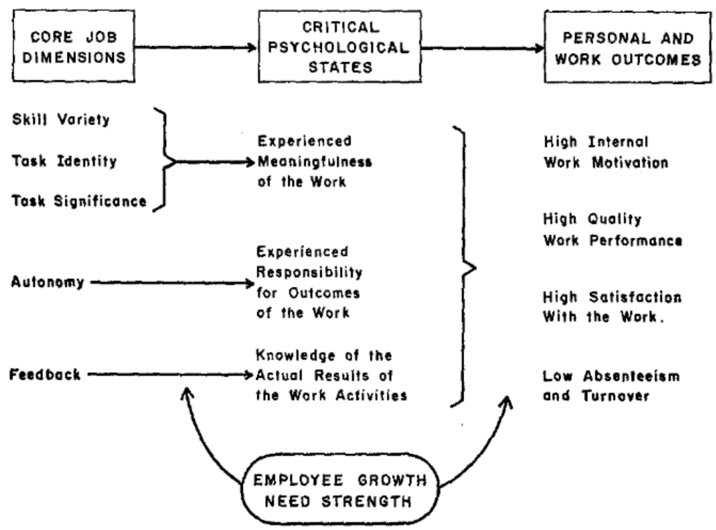



*Figure 1: The Job Characteristics Model.* This figure shows the different job characteristics that influence personal and work outcomes, as well as the psychological states causing the outcomes. (Hackman and Oldham, 1976)

### 2.1.2 Job Demands-Resources Model

Another notable framework is the Job Demands-Resources model (Bakker et al., 2003; Bakker and Demerouti, 2007; Demerouti et al., 2001). This model categorizes job attributes into job demands and job resources. Job demands are 'physical, social or organizational aspects of the job' that demand continuous physical or mental effort, leading to certain physical and mental costs. Job resources, on the other hand, are factors that help the employee to achieve their goals, counteract job demands, and promote the employees' personal growth and development (Demerouti et al., 2001). Resources can be social or organizational, such as job control, potential for qualification, participation in decision-making, task variety or support. These kinds of resources are called external resources. Resources can also be internal, as cognitive features and action patterns within the employee. Increased demands can lead to exhaustion and lack of resources to disengagement (Bakker et al., 2003). Although resources and demands each have their own effects, they also interact (see Figure 2). For this reason, it is important that these factors are considered while designing an organization and workplace. Since all occupations are unique and organized differently, the specific demands and resources will vary accordingly (Bakker et al., 2003). This theory is linked to the conservation of resources theory, which also links motivation to job resources (Bakker and Demerouti, 2007). Note that autonomy, feedback, and social aspects are considered crucial for employee productivity, just as they were in the JCM. In the context of WFH, job demands increase through more mental load as personal attributes like self-discipline and time management are called upon more. Further, social isolation and boundary blurring also increase stress and social isolation. However, WFH also brings resources, like autonomy and energy due to reduced commute.

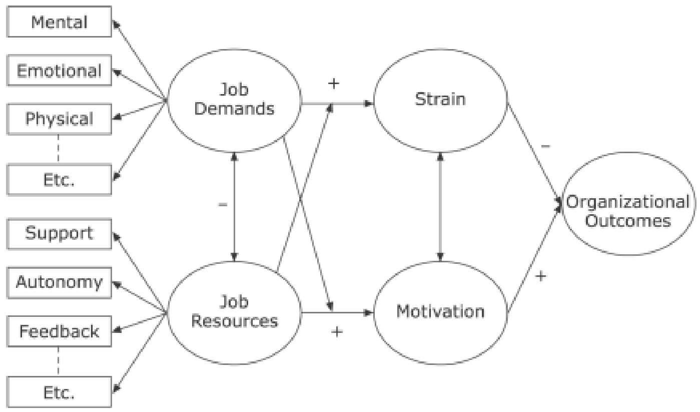



*Figure 2: The Job Demands-Resources Model.* This figure shows examples of job demands and resources, the relationship between the two and its causes. (Bakker and Demerouti, 2007)

### 2.1.3 Social Exchange Theory

According to the Social Exchange Theory (SET), social exchange is a series of interactions, generating obligations between individuals (Cropanzano and Mitchell, 2005). Usually, these interactions depend on each other and are contingent on behavior of the other party. This theory is relevant to the existing framework because, according to SET, when employers offer employees the possibility and flexibility of working from home, it should result in increased employee motivation. This could either offset possible negative productivity effects of working from home, or increase productivity. Caillier (2012) finds a positive relationship between teleworking and motivation. However, employees who work from home more frequently tend to be less motivated than those who telework less often. Work-life programs in the broader sense seem to have a positive effect on commitment if employees are satisfied with the program (Caillier, 2013a). However, the opposite has also been found: Caillier (2013b) and De Vries et al. (2019) don't find social exchange in return for teleworking.

### 2.1.4 Conservation of Resources Theory

Finally, I would like to point to the Conservation of Resources Theory (COR). According to this theory, individuals have resources that they want to hold on to (Hobfoll, 1989). Resources can take many forms: they can be tangible as well as intangible. Pensar and Rousi (2023) recall a list of job resources that have a positive effect on WLB, like flexibility, autonomy, social support from co-workers, supervisor support and family support. By holding on to their strengths and social attachments, individuals hope to succeed in keeping their resources in threatening situations. Resources bring safety, support and flexibility to individuals, which makes adapting to new situations easier (Hobfoll et al., 2018). According to the theory, resources typically exist in 'resource caravans' meaning that they are interconnected and also act this way: if you lose resources, you will likely lose more afterward, but the same holds for gains. This is referred to as gain and loss spirals (Pensar and Rousi, 2023). The harm caused by losing resources is considered greater than the benefits of gaining the same resources, and investing in resources helps prevent these losses (Halbesleben et al., 2014). This interplay makes resource investment a compelling and worthwhile endeavor.

This theory has been pointed to in the context of COVID (Franken et al., 2021). During the pandemic, individuals incurred losses while adapting to new technology, different workspaces, a higher workload, and changes in how they experienced contact with their team and maintained work-life balance at home. However, over time, gains were made in technology, workplace relationships, and productivity. Franken et al. (2021) suggest that adapting to a new way of working can take time, but it can be done with the appropriate resources and support systems identified through COR.

### 2.1.5 Influential Factors in Working From Home and Productivity

Having discussed different theories, I will focus on more specific influences on productivity while working from home. These factors are crucial for designing effective WFH policies, as well as understanding the relationship between WFH and productivity.

Job autonomy (also referred to as job control) entails freedom for an individual to choose how they do their work. This includes deciding when and how they work, but also how they make decisions (Hackman and Oldham, 1976). By definition, autonomy implies flexibility, which has been linked to increased worker engagement, resulting in higher productivity and satisfaction (Angelici and Profeta, 2024; Chatterjee et al., 2022; Saragih et al., 2021). Autonomy has also been associated with positive effects on productivity and employee engagement (Galanti et al., 2021). Furthermore, more job autonomy has been associated with a decrease in loneliness experienced by workers during the pandemic, by allowing them to integrate more social contact into their schedules (Wang et al., 2021). Having job control has also been associated with increased job satisfaction and reduced stress (Karasek Jr, 1979). During the COVID-19 pandemic, the increase in WFH led to greater autonomy (Galanti et al., 2021). Although remote work was compulsory and employees couldn't choose whether to work remotely, they did have some control over when they worked. This compulsory nature might have negative effects on productivity (Hackney et al., 2022). However, Saragih et al. (2021) finds positive effects of autonomy on productivity during the pandemic.

Besides changes in autonomy and flexibility of work, the shift to digital work changed feedback mechanisms drastically. Effective technology played a crucial role (Franken et al., 2021; Saragih et al., 2021). However, having computer skills does not seem to be important (Baruch, 2000). According to the JCM, lack of feedback changes the workers' knowledge of the quality of their results (Hackman and Oldham, 1976). According to Nakrošienė et al. (2019), reduced communication plays a large role in teleworking outcomes, leading to variations in results. Awada et al. (2021) find that the amount of communication matters for the productivity of remote workers. More communication is associated with higher productivity. The inverse relationship is also described. Difficulties in communication between colleagues have been found to affect productivity negatively (Gibbs et al., 2021).

During WFH, employees might experience increased isolation, which can be linked to higher stress and lower performance and satisfaction (Galanti et al., 2021). Although online means might play a positive role in increasing intercollegiate communication, it does not bring the same satisfaction, due to less closeness and intimacy (Franken et al., 2021; Wang et al., 2021). A proactive mindset caused by autonomy might play a positive role in initiating intercollegiate communication, and through this in reducing loneliness (Wang et al., 2021). As contact with colleagues decreased, the supervisor's role became more important (De Vries et al., 2019). Increasing supervisor contact allows employees to increase their performance and satisfaction, especially if they feel supported (Chatterjee et al., 2022; Golden and Veiga, 2008). Besides support, trust is also especially important (Nakrošienė et al., 2019). The relationship between job satisfaction and productivity is complex and multifaceted. Having high job satisfaction has been associated with higher productivity. Remote work can cause decreased work satisfaction, because of worsened WLB and higher stress (Sandoval-Reyes et al., 2021). Conversely, with increased satisfaction and productivity, job performance can decrease (Ramos and Prasetyo, 2020). Job stress is a negative influence on productivity (Ramos and Prasetyo, 2020). Therefore, managing the factors that contribute to job satisfaction is crucial for maintaining and enhancing productivity. Researchers have extensively explored how the amount of time spent working from home affects productivity outcomes. Self-reported hourly productivity may increase by increasing WFH, but it is not associated with the amount of hours worked (Deole et al., 2023). Positive effects of working from home on work effort (the difference between hours worked and hours employed) have been found (Gibbs et al., 2021; Rupietta and Beckmann, 2018). According to Bloom et al. (2015), the expected effect of WFH on hours worked is ambiguous, because it is determined through three channels: the attractiveness of breaks which is related to the work location, productivity at the location, and the attractiveness of more breaks because of less commute time. These factors determine the amount of breaks, which determines the amount of hours worked. In line with the SET model, the extra time should be used to work more in exchange for the flexibility of WFH. According to Kazekami (2020), there can also be too much WFH, reducing employees' productivity. Awada et al. (2021) and Baruch (2000) also find the context of work to be influential in productivity outcomes. Before COVID, increasing WFH had been associated with lower stress, and by that with higher performance. However, that did not directly have effect on the amount of hours worked (Rupietta and Beckmann, 2018). Gibbs et al. (2021) find an increase of hours worked, with a similar level of output. This means productivity went down. Awada et al. (2021) also find increased hours spent at work. By working from home, employees reduce their commute time, which, in line with SET, can be spent working (Saragih et al., 2021). Especially for employees commuting more than an hour during rush hour, productivity seems to improve (Kazekami, 2020).

But it is not only the workplace and the organization of the telework, personal characteristics also have effect on the outcomes. Employees with self-discipline and time-management skills are more likely to be successful in their WFH (Baruch, 2000; Wang et al., 2021). Self-discipline has been associated with higher productivity as well as with better WLB. Another influential personal characteristic is gender. Gender can be moderating between productivity and WFH (Farooq and

Sultana, 2022). There are also studies in which gender did not have this effect (Allen et al., 2015; Gajendran and Harrison, 2007). However, Gajendran and Harrison (2007) found that there might be an expectation for women to carry more of the housework while they stay at home.

## 2.2 Work From Home and Work-Life Balance

The previously discussed factors can not only directly enhance productivity in telework, but may also boost it by increasing life satisfaction (Kazekami, 2020). Since WFH impacts WLB, WFH might also influence overall life satisfaction. Kazekami (2020) finds positive effects from WFH on happiness and work satisfaction, as well as increased stress. He does not find that these affect productivity. As is repeatedly found in previous research, there is a positive relationship between WLB and productivity (Bloom and Van Reenen, 2006; Hobson et al., 2001; Konrad and Mangel, 2000). However, during COVID, Campo et al. (2021) did not find WLB to be a mediating factor in the relationship between WFH and job performance. Finding the relationship between WFH and WLB can be illustrative to the effect WFH can have on productivity.

### 2.2.1 Work Influences on Work-Life Balance

WFH can increase job satisfaction and WLB, which can in turn reduce stress. However, stress can also be increased due to the challenges of balancing work and home life, potentially decreasing life satisfaction (Kazekami, 2020). Karácsony (2021) finds an increase in job satisfaction and reduced stress, while Sandoval-Reyes et al. (2021) report increased stress and reduced WLB. Additionally, employees working alone experienced increased emotional exhaustion due to loneliness, which negatively impacted WLB (Becker et al., 2022; Karácsony, 2021). As previously mentioned, working from home increases job autonomy and inherently enhances flexibility. The influence of flexibility on WLB is unclear. Adisa et al. (2022) find negative effects, as well as increased stress, while Angelici and Profeta (2024) and Karácsony (2021) find improvements of WLB. According to Becker et al. (2022), employees that experienced high job control during WFH, had lower emotional exhaustion and could improve their WLB. However, Wang et al. (2021) argue that autonomy does not decrease conflicts between work and home life. Although it can help manage stressors associated with remote work, it may also blur the boundaries between professional and personal life, potentially creating additional challenges. During COVID, the planning of and autonomy at work were higher, but the workload itself also increased, causing more stress and worsened WLB (Adisa et al., 2022; Franken et al., 2021). Boundaries help when WLB worsens, but not for all employees (Adisa et al., 2022). Setting boundaries ensures that employees can keep their work and life separated, while also maintaining and maximizing the benefits of the found flexibility. Especially older employees are good at setting boundaries and have tactics they can use to this end (Scheibe et al., 2024). Supervisors showing family supportive behavior to their employees can increase WLB and performance, but by increasing monitoring, they can also increase stress and worsen WLB (Adisa et al., 2022; Campo et al., 2021). Workers that have a good relationship with their boss can increase their performance (Golden and Veiga, 2008). Whether WLB increases or decreases seems thus highly dependent on different factors, and outcomes are dependent on the elements examined (Campo et al., 2021; Juchnowicz and Kinowska, 2022). If negative effects are found, the effects can adjust over time and increase WLB (Franken et al., 2021).

### 2.2.2 Home Influences on Work-Life Balance

Factors originating from the home environment are just as crucial to WLB as those directly influenced by the employer. According to Baruch and Nicholson (1997), the home environment needs to be beneficial for work to make teleworking beneficial. However, Franken et al. (2021) argue that WFH has worsened the physical workspace. In general, during the COVID-19 pandemic, individuals found it difficult to balance home and work responsibilities (Saragih et al., 2021). With increased isolation both socially and professionally, it was easy to get distracted and to be tempted by counterproductive behavior (Nemteanu and Dabija, 2021).

A large contributor to the way home-life is designed, is the composition of the family. Single individuals are more likely to telework than individuals with a partner (Zhang et al., 2020). Individuals who did have partners, were highly affected by their partner working from home (Galanti et al., 2021). Having children in the home also has large effects. Zhang et al. (2020) finds that individuals without children are more likely to telework than individuals with children (Zhang et al., 2020). These individuals experience a decreased work-life conflict (Schieman et al., 2021). However, when asked, especially parents reported that they appreciated working from home (Angelici and Profeta, 2024). Additionally, German parents have doubled their WFH time over the last two decades (Arntz et al., 2022) However, individuals with children also experienced increased work-life conflict (Beauregard et al., 2019). The age of the children matters for the influence they have. Young children demand the most attention from their parents, which is associated with decreased WLB when working from home (Collins et al., 2021; Galanti et al., 2021; Nakrošienė et al., 2019; Schieman et al., 2021). Parents of young children reported working more hours, or lower their hourly productivity (Awada et al., 2021; Deole et al., 2023). Individuals with teenagers experienced the same effect as individuals without children (Schieman et al., 2021). However, on the positive side, WFH did increase the contact and cohesion within families (Baruch and Nicholson, 1997).

Personal attributes play a role in how WFH affects WLB. Individuals who prefer clear separation between work- and home-life had more difficulties with WFH (Adisa et al., 2022). Becker et al. (2022) specifies this further: individuals with low preference for separation increase their WLB, but those with a high preference decrease their WLB. Furthermore, concentration as well as discipline and time-management skills are needed when working from home (Baruch and Nicholson, 1997).

Another personal attribute that influences the relationship between WFH and WLB is gender. Although Schieman et al. (2021) reported no significant differences between gender patterns, other studies suggest the opposite. Fan and Moen (2022) find that women change their hours more than men, and additionally find that women without advanced degrees will decrease their hours, while women who do have these degrees may increase their hours. In general, mothers reduced their work hours more than fathers during the pandemic, or (temporarily) quit working, even if both partners worked from home (Collins et al., 2021; Mooi-Reci and Risman, 2021; Zamarro and Prados, 2021). Although with the pandemic, more household responsibilities arose, they were not equally divided between partners (Collins et al., 2021; Dunatchik et al., 2021). However, men reported doing more household work since the pandemic (Angelici and Profeta, 2024). The literature is divided on who increased their parenting time more, but mostly points at an increased burden for women. According to Augustine and Prickett (2022), women ended up with a disproportionate burden from care tasks, even though both partners did increase their parenting time. The division of parenting time seems to be independent of the man's working situation (Del Boca et al., 2020). Zamarro and Prados (2021) also finds that women take on the primary burden of childcare, causing them psychological stress. Tomei (2021) also points at the increased burden for women, which is caused by teleworking reinforcing traditional gender roles. This effect is also found by Hjálmsdóttir and Bjarnadóttir (2021) and Lyttelton et al. (2020). Besides carrying more burden, women may also lose productivity (Farooq and Sultana, 2022), while before the pandemic no significant productivity differences were found (Feng and Savani, 2020). With respect to women taking on more of the caretaking role, Çoban (2022) also describes the risk of detaching women from work, and going back to traditional gender roles. In conclusion, men and women might be using their time at home differently, and by that, teleworking might have different effects on them (Rodríguez-Modroño and López-Igual, 2021). Arntz et al. (2022) finds that gender differences between parents can become smaller with WFH take up.

# 3 Theoretical Model

In this section, by comparing and synthesizing relevant studies discussed in the previous section, I form expectations about how WFH affects WLB, particularly regarding the number of hours employees work. I will build a theoretical model and formulate hypotheses for this research.

Both the JCM and the JD-R Model point at different elements needed for the motivation and performance asked, satisfaction wished for and strain caused by the work. Autonomy, feedback and support are repeated within the two and are also elements in which changes have been made through the pandemic. According to the JD-R Model, with the right resources, employees will be more motivated and better able to mitigate the negative effects of job demands. In the context of WFH, increased autonomy is expected to increase productivity, because of flexibility in scheduling work. In the JD-R model, resources like technical support and clear communication can enhance performance and mitigate job strain. Both models emphasize the role of job characteristics and resources in determining productivity and satisfaction. Higher WLB is expected to increase satisfaction and reduce stress, which positively impact productivity.

The COR theory predicts employees to hold on to those elements that they perceive as resources from their job and private life, and use them in the new COVID situation, but also in the Post-COVID period. Specifically, these resources include autonomy, flexibility, feedback, and support, which are critical for maintaining motivation and performance while mitigating job strain. As WFH was mandatory for a large part of workers, the already existing and expanding WFH trend increased enormously. With this sudden and mandatory new way of working, adjustment was necessary, and the abruptness of it possibly brought difficulties (Eurofound, 2021). A large influence during the mandatory WFH is distractions at home. For individuals with a partner or a family, this meant more individuals in the house. Especially young children are expected to affect the productivity of their parents, because they need the most attention and support. Aside from this, the workplace at home might bring its own distractions with home responsibilities.

The SET predicts that providing the opportunity for flexibility generates obligations between employer and employee, and can motivate employees to work hard for their boss. Mandatory WFH might not evoke such a feeling of obligation, as it is not a provided opportunity. After the pandemic, this gratitude might return, when becomes optional again. Combined with the adjustment period being completed and negative influences from the period decreasing, this might increase the benefits of WFH both for employer and employee. Franken et al. (2021) expects that after COVID, positive effects of WFH might be found, because of the adjustment time. Further, without the mandatory nature of WFH, workers and employers can find an optimal level of WFH, which increases workers' WLB and productivity. Above that, negative effects from pre- or during COVID might not be directly applicable to the Post-COVID period (Wang et al., 2021). Especially with distractions in the house becoming less with children being at school or care during the day, and flexibility allowing partners to make agreements on working home and tasks. Women are expected to have more results than men, because they have to carry more of the household burdens. Creating more WLB for them specifically is expected to influence outcomes.

The amount of time worked shows work effort, which is an important determinant for productivity (Gibbs et al., 2021; Rupietta and Beckmann, 2018). Through the literature, there are a few possibilities to which mechanism weighs heaviest in determining outcomes. Workload during COVID went up, but might be going back to its normal levels afterward, thus increasing and then decreasing. Productivity is determined by a lot of factors; if these cause productivity to go down, this might increase hours worked. But, hours worked can also go up due to gratefulness for flexibility. This effect would be expected after COVID, without mandatory WFH, while the first effect (the increase in hours worked due to a decrease in productivity) would be more likely during COVID. How all factors mentioned are experienced and weighed by individuals might differ. Karácsony (2021) finds that negative effects of working from home do not weigh up against the positives, but this can be different between sectors, genders, and even countries.

### 3.1 Hypotheses

All of this leads to the expectations of what I will find with the analysis discussed in the next section. Wang et al. (2021) argue that the unique context of the pandemic might change assumed theoretical relationships, and therefore that the traditional way of looking at things might offer limited insights into reality. In practice, this means that results of COVID 1 and COVID 2 might not be extendable into Post-COVID, and that periods might need to be interpreted differently.

Firstly, through the JCM, I expect that flexibility and autonomy enable employees to work during their most productive hours and balance home and work life more effectively. However, these factors might also increase total working hours due to the overlap of work and home responsibilities. Another increase might be expected through reduced feedback, reducing also the knowledge of work quality. As employees don't know whether they have met the expected standards, they might work more hours to compensate. Further, the JD-R model predicts that increased job resources (autonomy) may help employees to manage higher demands, although still leading to longer working hours. COR then predicts that by conserving energy through less commute time, more energy can be invested into work hours. There is also more time available for working, increasing the amount of hours worked. As these influences are strongest during COVID, I expect the highest amount of average hours worked during COVID 2. Finally, through SET, employees that get more flexibility through WFH, may feel obligated to return the favor by putting in more hours, but this effect is strongest in the Pre- and Post-COVID periods, because in the others, WFH is mandatory. From this dataset, I find that men work more full-time and women work more part-time (see Appendix A.4). As women are theorized to decrease their hours more than men, I expect this to work through in the part-time and full-time split. Based on the emphasis on autonomy in both JCM and JD-R, as well as the reciprocity from the SET and the saved energy from commuting, I expect that:

*H1: Employees working more time from home per week, end up working more hours per week.*

Second, I expect that having home responsibilities might be an influential factor in the decision of how many hours an employee wants to work. As WFH can increase WLB and make it easier to combine home- and work-life, employees that work part-time for this reason, might benefit from WFH. Both the JCM and the JD-R model predict that working from home offers greater flexibility through the increased autonomy, enabling individuals to manage their home responsibilities alongside their work tasks without needing to cut down on working hours. Furthermore, eliminating the daily commute saves time and energy, allowing these individuals to spend this time and energy on their home duties. Both factors allow hours worked to increase. This means that chances of working part-time, decrease. Individuals with a higher *Household Division Index* might experience a more positive effect of WFH, because they benefit the most from the increased flexibility. This means that individuals with a higher *Household Division Index* reduce their chances of working less even more. At the beginning of COVID, the effect might be smaller than after COVID, as WFH has been more integrated, and individuals might have changed their behavior over time by integrating more WFH into their lives. For Hypothesis 2, again the same effects between part-time and full-time are predicted as for Hypothesis 1. Part-timers are hypothesized to work less to take care of the home, and they might thus benefit more from WFH, as it allows them to increase work hours. Combining the JD-R model and the COR theory, I expect that by increasing WFH time, employees can be more efficient with their resources, which allows them to manage home responsibilities without having to reduce their work hours to part-time:

*H2: Employees who increase their WFH, decrease their chances of having to work part-time to take care of the household.*

Besides home responsibilities, employees may also have childcare responsibilities that can influence the number of hours they work. In other words: employees with children might reduce their hours to be able to take care of their children. WFH, and especially the autonomy that comes with it, can help employees to balance their parenting duties with work, reducing the need to cut back on work hours. Again, both JCM and JD-R predict that this is possible through higher flexibility. I expect that combining childcare and work through WFH, reduces the likelihood of having to reduce work hours to take care of children. Parents with a higher *Childcare Division Index* might experience a higher effect of WFH, because they take the most benefit from the increased flexibility. The same is expected for individuals taking care of more children. Working from home allows parents to save time and energy spent commuting, which can be spent on children. During COVID, children were often at home, which might reduce the positive effect of WFH. After COVID, children went back to school and parents were more accustomed to WFH, allowing the effect to increase. This effect is hypothesized to be stronger for part-time employees, if they decreased their hours to take care of children. However, as both full-time and part-time employees will have to deal with children being home during COVID, period effects are expected for both full-time and part-time employees.

*H3a: Employees who increase their WFH, decrease their chances of having to work less to take care of children.*

Not only can WFH reduce the likelihood of parents cutting back on their hours, but it can also help to minimize the reduction. I expect that the reduction becomes smaller with increasing WFH. For Hypothesis 3, I again expect the same differences between full-time and part-time as I did for Hypotheses 1 and 2. As part-timers are hypothesized to reduce their hours more often than full-timers, they are also expected to experience more positive effects from WFH.

*H3b: Employees who increase their WFH, can reduce the number of hours they work less to take care of children.*

By looking at both Hypotheses 3a and 3b, I can provide a more nuanced analysis of the impact of WFH and the size of its effect.

# 4 Data and Methodology

In this section, I discuss how I outline the research design and which analyses are used and in what way. Detailing my design makes the research reproducible as well as transparent, before results are presented. With this research, I investigate the impact of working from home on the amount of hours employees work. The analyses used allows- me to examine the impact through balancing work- and home-life, for parents and non-parents, as well as full-time and part-time employees working in different sectors. Next, I explain the data used in the study, including how it was selected and transformed. Finally, I discuss the analytical framework applied and estimation techniques I used.

## 4.1 Research Design

For this research, I use a quantitative research design. This means that I focus on statistical analysis with quantitative data to investigate the relationship between WFH and WLB, especially focussing on the number of hours worked. I chose this design because it allows me to test my hypotheses with precision using a large number of data points. It also allows me to provide a numerical answer to my research question, which is easier to interpret and relay when discussing possible consequences and implications of the outcomes. With this study, I illustrate possible mechanisms influencing WLB and the number of hours employees work. Further, I look at the impact of different variables on this relationship, and show explanations for it.

## 4.2 Data Source

For this research, I use data from the LISS Panel (Longitudinal Internet studies for the Social Sciences) managed by the non-profit research institute Centerdata (Tilburg University, the Netherlands). I chose LISS Panel data because LISS offers a more up-to-date data set than others like the European Working Conditions Survey. This allows me to look at the first after-effects of teleworking because of COVID-19 on WLB, up until 2023. Another benefit of the LISS data is that it provides extensive background information on respondents, as well as other studies done on the same sample.

The LISS Panel consists of 5,000 households and 7,500 individuals invited to join the panel (Centerdata, 2023). The ability to join is only based on being invited. Who is invited to the panel is determined by Statistics Netherlands, by drawing a true probability sample of households from the population register. LISS data is available for researchers and policymakers with access to the archive. The LISS Panel consists of several 'Core Studies' and single wave studies. A wave represents a specific year of data collection. Core studies are longitudinal studies, consisting of multiple waves, repeated each year since 2007. Two of these core studies are used for this research. The first one is 'Family and Household' and the second 'Work and Schooling'. I have used six waves per core study for this research, for the years 2018-2023. These are the waves 11-16. For the 'Family and Household' study, the last wave had not been published yet at the time of the research. After contact with the researcher on that study, I was allowed to receive the necessary data for my analysis separately. In addition to the core studies, I used the Background Variables survey conducted in April or May for each wave, which corresponds with the Work and Schooling wave. Since only the birth year is taken into account, the specific timing of the survey does not matter. I selected the survey timing based on which option resulted in the fewest lost observations. I only used these two months because of efficiency reasons. By merging, I assume that all measurement was done in the months April and May during the reference period. Since this research is based on survey data, all values are self-reported.

### 4.2.1 Data Structure and Volume

The LISS Panel allows for direct download of STATA files, which makes it easy to import data for analysis. STATA files are organized in a table format with rows and columns. A row represents an individual and a column represents the different variables, based on the survey questions. For this research, I used a total of 18 data files, consisting of six waves, over two core studies and the background surveys. Per data file, a different amount of answers was registered. Immediately, this means that not all participants to the study answered every survey, and thus not all participants can be followed over the six-year course of surveys this research uses. This panel is thus an unbalanced panel. The final dataset, with all waves combined, contains 3,226 unique respondents. In total, there are 8,621 observations.

### 4.2.2 Key Variables

In this research, I am interested in finding the relationship between WFH and the amount of hours employees work. To that end, I have formulated three hypotheses in the Theoretic Model.

The dependent variable I will be using for Hypothesis 1 is *Hours Worked*. This variable is an integer, and is given as an answer through the Work and Schooling survey. The variable indicates the average amount of hours an individual works per week. Answers were allowed to range between 0 and 168 hours.

In these hypotheses, I look at reasons why and if individuals work less in relation to care. For Hypothesis 2, I will look at individuals working part-time, because of home related care tasks (*Working Less for Home*). They were asked the following question: “You work(ed) for less than 36 hours. Can you indicate for what reason(s) you work(ed) parttime?”. The answers I used to construe the variable are: “due to a (changing) family situation at home” and “due to other activities at home”. The data for this variable comes from the Family and Household survey, and is binary. It takes value 1 if someone works less than 36 hours due to home tasks, and 0 otherwise.

For Hypothesis 3, I look at whether individuals work less because they care for a child or children. I will examine both whether they reduced their work hours for this reason, and by how much. The first, *Working Less for Children*, is a binary variable that takes value 1 if someone works less because they care for children, and 0 otherwise. This variable comes from the Family and Household survey, and is measured through the question “are you currently working less in order to care for your children and/or grandchildren?” This answer is binary, and takes value 1 if the respondent works less because of childcare, and 0 if not. If this question is answered with yes, the respondent can provide the amount of children they care for and the amount of hours they work less because of childcare. To look at the size of the reduction, I use the variable *Hours less Childcare*. For this, I make use of the question “How many hours per week are you working less on account of the care for your children?". This question also comes from the Family and Household survey, and is numerical, ranging between 0-40 hours.

The independent variable illustrates the presumed influence on the amount of hours worked. As I focus in this research on WFH, and specifically the amount of time individuals WFH, this is reflected in the independent variable. For the main analysis, I will be making use of the categorical variable *Days WFH*. For this variable, individuals were asked in the Work and Schooling survey whether they had a (partial) work from home day. This question could be answered through four options: “no”, “yes, less than one day per week”, “yes, about one day per week” and “yes, more than one day per week”. Because the categories are not distanced identically from each other, I have created a categorical variable that uses dummy variables for the different levels to create the independent variable.

For an additional analysis, I will look at *Hours WFH* instead of *Day WFH*. This variable is an integer, and it provides the average amount of hours per week someone works from home. The amount of hours WFH range between 0-48 hours. This data is available from 2020 onwards and comes from the Work and Schooling survey.

Because I will be using a Fixed Effects Regression, certain variables do not need to be included as controls. Variables like gender, education and other background variables that are constant over time are accounted for with individual fixed effects and will thus not be separately be included.

The first personal control variable, *Age*, is taken from the Family and Household Survey. It represents the age of the respondent at the time the survey was filled in. This variable is added because it can be of predictive power to the amount of hours someone works.

Second, I know whether someone has a *Partner* and if they live together with this partner (*Live Together*). The LISS Panel assumes that partners are together for more than three months. *Partner* itself is not used as control, but used to code other variables. The data for these variables comes from the Family and Household survey. Both are binary variables, taking 1 for partner or living together, and 0 if not. Whether someone has a partner can play a role in the division of household and care taking tasks, specifically if they live together with their partner.
Home related control variables see to respondents’ home life. Specifically, on childcare responsibilities and the division of household tasks. I am interested in the amount of children someone has, and the amount of care they receive. Both give an indication of the pressure of care taking on parents during the workday. Firstly, I determine whether someone is a *Parent*. It is a binary variable. If someone has ever had children (including step-, adoptive or foster children), Parent takes value 1, if not, it takes 0.

Besides whether someone is a parent, I know how many living children the respondent has. Children can be in the age categories between 0 and 4 (*Children 0-4*), between 5 and 11 (*Children 5-11*) and 12 and older (*Children 12+*). All categories are integers. These categories overlap with the assumed need for care. Children in the first category will probably receive the most hands-on care and take the most unpaid work. The second category includes children of primary school ages. They are in school part of the day, and receive care the other part of the day. The last group consists of children of high school ages and older. I assume this group will receive the least care outside of school.

I also included a control variable that indicates the number of part-days childcare utilized by a respondent (*Part Days Childcare*). This is an integer. All information on children is taken from the Family and Household survey.

Pressure of childcare related tasks as well as for household responsibilities is measured through created indexes. The higher the index, the higher the share of responsibilities the respondent holds or performs. The index indicates the quantity of tasks and responsibilities the individual has in household matters related to the care for children. I created two separate indexes: *Household Division Index* and *Care Division Index*. Both are based on questions in the Work and Schooling survey. Adding both *Care Division Index* and the different amounts of children in their respective age categories shows both the amount of children living at home, as well as the division of tasks.

Work related control variables see to the variables that say something about the work life of the respondent. The variable *Employment Sector* provides information on the sector in which the respondent works, or had their last job. It is a categorical variable consisting of the following categories: Agriculture, forestry, fishery or hunting; mining; industrial production; utilities production, distribution and/or trade; construction; retail trade; catering; transport, storage and communication; financial; business services; government services, public administration and mandatory social insurances; education; healthcare and welfare; environmental services, culture, recreation and other services; other. This control variable allows to look for sector differences in working from home and working hours. This variable is taken from the Work and Schooling survey.

*Commute Time* is measured in minutes and provides information about the respondents' one-way travel time to work. If they do not have the same travel times every day, they give an average. Mode of transport is not recorded or taken into account. *Commute Time* is an integer between 0 and 240 minutes. Commute time is influential in the WLB of employees. WFH can save on commute time, creating more opportunity for a better WLB. This variable is taken from the work schooling survey.

*Satisfaction with Working Hours* is a scale variable, from 0-10, where individuals can choose the integer that best represents their satisfaction with their working hours. 0 means the respondent is not at all satisfied with their working hours, 10 means that they are fully satisfied. This control variable provides information on whether a person is satisfied with their current hours. This is important to add, because it can give information on whether respondents would like to work different hours, which can be signalling information on their work-life balance. This variable is taken from the Work Schooling survey.

*COVIDPeriod* is a categorical variable that consists of dummy variables for the different periods and allows me to look at COVID-related shocks and influences, while also controlling for other time varying shocks with t.

### 4.2.3 Defining the Sample

The sample exists of individuals of working ages (15-75 years old), that are able to work CBS (2024a). However, I do exclude unemployed individuals, as I am interested in the effects on employees. This specifically also includes individuals that are performing unpaid work while retaining their allowance or benefits, individuals who do not have an obligation to search for a new job, individuals who are first-time jobseekers (because they do not have a work-life balance life yet), students, working students, individuals living off private means, retirees, individuals disabled for work and individuals doing voluntary work. Furthermore, it includes individuals who answered they do "something else" as their primary occupation, as well as individuals who are "too young to have an occupation". Moreover, individuals who are self-employed are not included. Individuals providing informal care are excluded, as their work-life balance does not align with the focus of this research. Additionally, individuals on parental leave are excluded, as their unique circumstances differ significantly from the study's scope and could introduce biases. Individuals whose full-time job was 36 hours or less were dropped, because they interfere with the dependent variables on H2. Finally, individuals that indicated having a side job besides their main employment, or an own business besides their main employment were dropped. The reason for this is that the amount of hours they work is unclear, as they only provide the amount of hours for their main job. This does not only influence their amount of hours worked, but also their whole life, especially their WLB, which might introduce bias into the analysis. Another reason to exclude individuals with a full-time job of 36 hours or less, is that I split the sample into full-time and part-time workers. For this end, I created a new variable *full-time*, to make a difference between the two analyses. To make the split, I assume that a full-time workweek is 36 hours or more. I create a variable that takes value 1 if the respondent is employed for more than 36 hours per week in the year they are first present in the panel, and 0 otherwise. I base this on the respondent's answer to the question for how many hours they are employed in the Work and Schooling survey. I use first observation classification. This means that the classification, made based on the first observation, is maintained over all observations of this individual. Doing this allows me to look at the progress of individuals who initially are full-time or part-time employees. I can maintain consistent groups that allow me to analyze long term implications of teleworking. I don't make the variable dynamic, because this creates instable groups. Stable groups provide a basis for consistency in analysis as well as a more focussed analysis. Furthermore, if I make the groups dynamic, I cannot analyze what happens with individuals working part-time because of responsibilities at home because they would switch groups. As shown in Appendix A.2. A transition table looks at whether individuals have changed their classification over time. This table shows that there is a high level of stability in the sample, meaning that most individuals stay within their original classification. The regressions are run based on either full-time = 1 or full-time = 0. Splitting it manually instead of adding a full-time control allows me to compare the influences and effects the separate groups deal more precisely.

I do not exclude individuals who are not parents, because having both in the sample allows me to compare individuals with and without children. However, individuals who care for grandchildren are dropped, because this interferes with the dependent variable for H3.

### 4.2.4 Data Cleaning

Cleaning the data before analysis allows me to make conclusions based on accurate and complete data. With cleaned data, I can analyze the data efficiently, without outliers or inaccurate data points. This decreases the chance of biases and errors in the analyses and conclusions, and produces more reliable insights.

First, the data from different surveys within the same year are merged and cleaned. After this, the cleaned and merged files for all years are appended. Some cleaning steps were performed after the appending of the datasets. I look at missing values when the datasets are merged and appended, because this allows me to have a clearer image of how many missing values there were per variable in total, and not per wave, so that I can take appropriate measures. Additionally, I made sure all unemployed individuals were actually dropped. I created a binary variable *Employed*. If someone was employed for more than 0 hours, it takes value 1, and 0 if not. This variable is not used as control, but used to code other variables in the dataset. Individuals with value 0 were dropped. Other changes I made after appending were changing variables' labels, to increase the ease of analysis.

For the first dependent variable, *Hours Worked*, if participants indicated not knowing how many hours they work on average, their answer was replaced with the answer to the question for how many hours they are employed. If the amount of hours employed was missing, it was set to zero. This was done because not working corresponds with the requirements of being asked this question. If someone was not employed, their average amount of hours worked was replaced with 0, because I am interested in their current working hours, and not for a past job. If someone worked more than 80 hours per week, it was assumed an outlier and removed.

For the second dependent variable *Working Less for Home*, a new variable is created. This variable is binary, and takes value 1 if the individual works less than 36 hours per week because of responsibilities at home, and 0 if not. Whether a respondent has home responsibilities according to this variable is linked to a question on the reason of working part-time. For this question, a list of options was given and (multiple) applicable answers could be given. The answers were all binary. From this list, I chose the two options that relate to home responsibilities: "family situation at home" or "other activities at home".

The independent variable, *Days WFH* consists of four not-identically spaced categories as answers to the question. To make analysis easier, I created dummy variables for the answer categories, and used the first category (no working from home day) as the reference category. If work from home day was missing, I replaced it with no work from home day, because this question was asked to everyone besides working students. If someone is not employed, the value of WFH-day is replaced with 0.

*Hours WFH* was provided by the respondents from 2020 and later years. This variable is used in the additional analysis.

Missing values in *Age* were dealt with by replacement with the calculated age based on the year the survey was taken and the respondents' birth year. If this resulted in an individual having the same age in multiple waves, I incremented their age by one year in the second occurrence of the duplicate waves. After correction, ages falling outside the sample brackets were dropped. Observations with age under 15 or higher than 75 are dropped, because they fall outside the sample.

If the value for *Partner* was missing, the observation was dropped. Missing values in the answer to the question whether someone had the same partner as the year before, were replaced with "no" if someone did not have a partner this year. This value was needed for replacing the answer to the question of whether someone lives together with their partner (*Live Together*). Only individuals who responded that they have the same partner as the previous year were asked whether they live together with their partner. The survey's assumption thus seems to be that if you do not have the same partner as the last year, you are not living together. In order to remain with this assumption on which the questions were asked, but also to fill in the missing values this creates, I set living together to "no" for individuals who did not have the same partner as last year. There were two observations remaining with a missing value for living together. These were dropped as the cause could not be determined and it was a not-influential amount of observations.

I created a new variable *Parent*, a binary variable taking value 1 if someone ever had any children, and 0 otherwise. If someone is not a parent, I replaced the amount of children with 0.

Related to household tasks, the survey asks respondents living together with their partner about the division of six subtasks of household tasks. Participants are asked about the distribution time spent on food preparation, laundry, house cleaning, odd jobs in and around the house, financial administration and grocery shopping between them and their partner. From these questions, I created a variable *Household Division Index*, indicating the pressure on the respondent related to household tasks. Points were given related to the answers respondents could choose:

1. "I do a lot more than my partner"
2. "I do more than my partner"
3. "We do roughly the same amount of work"
4. "My partner does more than I"
5. "My partner does a lot more than I"
6. "It is completely being outsourced"

In order to create an index that projects a higher number (representing a higher burden) if someone is responsible for a lot of the housework, values are matched. If a task is being executed by the partner, or is outsourced, it gets value 0, because it does not add to the household burden of the individual. Categories 1-3 are matched with scores 3-1 respectively to represent the burden added to the individuals' workload. If the respondent did not live together with a partner, they got a score three for all tasks. Remaining missing values were set to 0. Creating the index in this manner, assumes that all tasks convey the same burden to the executor.

For care related tasks, four questions were asked about the distribution of care tasks related to play, driving their children to school or other places, talking to their children about school problems and taking them on small outings. For care related tasks, another index was created. From these questions, I created a variable *Care Division Index*, indicating the pressure on the respondent related to care taking tasks. Because I am looking at the pressure of current responsibilities, I only include the answers and questions based on the current ages of the children. Respondents are asked to choose from:

1. "I do a lot more than my partner"

2. "I do more than my partner"

3. "We do roughly the same amount of work"

4. "My partner does more than I"

5. "My partner does a lot more than I"

6. "It is completely being outsourced"

For years 2020 and further, another sixth category is included, indicating that the question is not applicable. Again, values are changed in order to represent the burden of tasks. Categories 1-3 represent values 3-1, and categories 4 and 5 value 0. For the years when category 6 was included, it also received value 0. These values are given for the same reasons as previously. This index is called *Care division*. Respondents without children get value 0 for all tasks, because they do not have these responsibilities.

Both indexes are added as control variables, to make sure the analysis focuses on the effect of WFH on hours worked, and is not influenced by task division within the household. As explained in the Hypothesis section, I expect different effects for different household and care divisions, and so by controlling for them, I can isolate the effect of WFH on hours worked.

For information on children and their assumed care needs, I created three categories: *Children 0-4*, *Children 5-11*, and *Children 12+*. These categories overlap with the assumed need for care. The first category will probably receive the most hands-on care and take the most unpaid work. The second category are children of primary school ages. They are in school part of the day, and receive care the other part of the day. The last group is children of high school ages and older. I assume this group will receive the least care outside of school. For external care, I look at the amount of part-days someone makes use of care options. If someone makes use of a toddler playgroup or nursery, child daycare, pre-school, after-school care, host parent, a babysitter, or another care option, the amount of part-days is recorded, otherwise it is set to 0.

If *Employment Sector* had value -9, the respondent did not know in which category they fell. This question was only posed to individuals with a job. For this reason, I replaced the value with category ‘other’, as it was unclear what sector someone was in. I can keep the observations without dropping.

I dropped observations with missing values for *Satisfaction with Working Hours* and *Commute time*, as well as for *Live Together*. I chose to handle these missing values this way, because the proportion was manageable enough and because imputation could introduce bias.

Finally, for *COVIDPeriod*, I created a new variable, with categories based on the year of the survey:

1. Pre-COVID (data from 2018 and 2019)
2. COVID1 (data from 2020)
3. COVID2 (data from 2021)
4. Post-COVID (data from 2022 and 2023)

These categories were created to control for the time period in which surveys were taken with the context of COVID-19.

For binary variables, most variables were coded in such a way that ‘yes’ was assigned value 1 and ‘no’ value 2. For easier interpretation, these were changed into 1 and 0 respectively. I did this for *Partner*, *Live Together*, *Taking Care of Children*.

### 4.3 Summary Statistics

Summary statistics give an initial understanding of the used data, and highlight some relationships and trends that might be influential for understanding further analysis.

The distribution of respondents across the different COVID periods is as follows in Table 1. Note that Periods COVID 1 and COVID 2 seem to be smaller than Pre-COVID and POST-covid. However, the latter exist of 2 years, and former exist of 1 year.

**Table 1.** *Summary statistics for COVID periods*

| COVID Period | Freq. | Percent | Cum. |
|---|---|---|---|
| Pre-COVID | 2,829 | 32.82 | 32.82 |
| COVID 1 | 1,505 | 17.46 | 50.27 |
| COVID 2 | 1,439 | 16.69 | 66.96 |
| Post-COVID | 2,848 | 33.04 | 100.00 |
| Total | 8,621 | 100.00 | |

*Note.* The table shows the amount of observations in each different COVID-19 period analyzed in the research. "Pre-COVID" refers to 2018 and 2019, "COVID 1" represents 2020, "COVID 2" denotes 2021, and "Post-COVID" signifies 2022 and 2023. Freq. indicates the number of observations in each period, Percent shows the proportion of each period relative to the total sample, and Cum. represents the cumulative proportion up to each period.

Table 2 presents the split between observations of full-time and part-time employees in the sample. Note that this table shows the division based on first observation classification. As shown in Appendix A.2, classifications do not change much over time.

**Table 2.** Split Between Full-Time and Part-Time Employees

| Employment Status | Freq. | Percent | Cum. |
|---|---|---|---|
| Part-time | 3,314 | 38.44 | 38.44 |
| Full-time | 5,307 | 61.56 | 100.00 |
| Total | 8,621 | 100.00 | |

*Note.* The table shows the amount of observations per employment status analyzed in the research. "Part-time" refers to individuals employed for less than 36 hours per week, while "Full-time" denotes individuals employed for 36 hours per week or more. Freq. indicates the number of observations in each period, Percent shows the proportion of each period relative to the total sample, and Cum. represents the cumulative proportion up to each period.

Table 3 presents summary statistics on the dependent and independent variables for the entire sample, to provide a clear overview of the data and sample characteristics. Negative values to "within" occur if an individual finds their values to decrease and increase, where the decrease is projected by the negative value. To compare between full-time and part-time workers, the same tables are provided for this split.

**Table 3.** Dependent and Independent Variables

| **Variable** | **Mean** | **Std. Dev.** | **Min.** | **Max.** | **Observations** |
|---|---|---|---|---|---|
| **Hours Worked** | 32.170 | 13.661 | 0 | 80 | N=8621 |
| Between | | 11.364 | 0 | 70 | n=3226 |
| Within | | 8.492 | -17.830 | 75.503 | T-bar = 2.67235 |
| **Days WFH** | 0.706 | 1.136 | 0 | 3 | N=8621 |
| Between | | 1.037 | 0 | 3 | n=3226 |
| Within | | 0.571 | -1.794 | 3.206 | T-bar = 2.67235 |
| **Less than 36 due to home** | 0.001 | 0.034 | 0 | 1 | N=8621 |
| Between | | 0.039 | 0 | 1 | n=3226 |
| Within | | 0.021 | -0.499 | 0.801 | T-bar = 2.67235 |
| **Working less for children** | 0.087 | 0.282 | 0 | 1 | N=8621 |
| Between | | 0.255 | 0 | 1 | n=3226 |
| Within | | 0.154 | -0.746 | 0.920 | T-bar = 2.67235 |
| **Hours less childcare** | 0.827 | 3.132 | 0 | 40 | N=8621 |
| Between | | 2.861 | 0 | 31 | n=3226 |
| Within | | 1.744 | -18.373 | 23.494 | T-bar = 2.67235 |

*Note.* This table presents the summary statistics for the dependent and independent variables for this research. It looks at the whole sample. N = Total number of observations; n = Number of groups; T-bar = Average number of observations per group. "Between" represents variation across individuals, and "Within" represents variation within individuals over time.

**Table 4.** Dependent and Independent Variables (full-time = 1)

| Variable | Mean | Std. Dev. | Min. | Max. | Observations |
|---|---|---|---|---|---|
| **Hours Worked** | 36.600 | 13.379 | 0 | 80 | N=5307 |
| Between | | 9.699 | 0 | 70 | n=1875 |
| Within | | 9.647 | -13.400 | 79.933 | T-bar = 2.8304 |
| **Days WFH** | 0.829 | 1.193 | 0 | 3 | N=5307 |
| Between | | 1.098 | 0 | 3 | n=1875 |
| Within | | 0.608 | -1.571 | 3.329 | T-bar = 2.8304 |
| **Less than 36 due to home** | 0.000 | 0.000 | 0 | 0 | N=5307 |
| Between | | 0.000 | 0 | 0 | n=1875 |
| Within | | 0.000 | 0 | 0 | T-bar = 2.8304 |
| **Working less for children** | 0.023 | 0.149 | 0 | 1 | N=5307 |
| Between | | 0.116 | 0 | 1 | n=1875 |
| Within | | 0.098 | -0.811 | 0.856 | T-bar = 2.8304 |
| **Hours less childcare** | 0.171 | 1.312 | 0 | 23 | N=5307 |
| Between | | 0.916 | 0 | 13.333 | n=1875 |
| Within | | 0.874 | -13.163 | 15.504 | T-bar = 2.8304 |

*Note.* This table presents the summary statistics for the dependent and independent variables for this research. It looks at employees labeled full-time. N = Total number of observations; n = Number of groups; T-bar = Average number of observations per group. "Between" represents variation across individuals, and "Within" represents variation within individuals over time.

**Table 5.** Dependent and Independent Variables (full-time = 0)

| Variable | Mean | Std. Dev. | Min. | Max. | Observations |
|---|---|---|---|---|---|
| **Hours Worked** | 25.076 | 10.821 | 0 | 60 | N=3314 |
| Between | | 9.422 | 0 | 56.667 | n=1351 |
| Within | | 6.211 | -9.924 | 65.076 | T-bar = 2.453 |
| **Days WFH** | 0.510 | 1.008 | 0 | 3 | N=3314 |
| Between | | 0.904 | 0 | 3 | n=1351 |
| Within | | 0.506 | -1.990 | 3.010 | T-bar = 2.453 |
| **Less than 36 due to home** | 0.003 | 0.055 | 0 | 1 | N=3314 |
| Between | | 0.060 | 0 | 1 | n=1351 |
| Within | | 0.034 | -0.497 | 0.803 | T-bar = 2.453 |
| **Working less for children** | 0.190 | 0.392 | 0 | 1 | N=3314 |
| Between | | 0.348 | 0 | 1 | n=1351 |
| Within | | 0.214 | -0.643 | 1.023 | T-bar = 2.453 |
| **Hours less childcare** | 1.878 | 4.580 | 0 | 40 | N=3314 |
| Between | | 4.086 | 0 | 31 | n=1351 |
| Within | | 2.587 | -17.322 | 24.545 | T-bar = 2.453 |

*Note.* This table presents the summary statistics for the dependent and independent variables for this research. It looks at employees labeled part-time. N = Total number of observations; n = Number of groups; T-bar = Average number of observations per group. "Between" represents variation across individuals, and "Within" represents variation within individuals over time.

Average hours worked for full-time employees is around 36 hours, with a within-deviation of almost 10. This means that individuals labeled as full-time show significant variability in their hours worked. For part-time employees, this is 25 hours on average, with a slightly lower within-deviation of almost 7. Further, the table provides a first indication that full-time employees have more WFH Days on average than part-time employees. Overall, very few individuals worked less for home responsibilities. Full-time employees do not work less or start to work less for home responsibilities. Part-time employees do work less for this reason, but also remain close to the mean of 0, with little standard deviation between individuals. Standard deviation within individuals is higher, suggesting that changes in WFH have a more significant impact on *Working Less for Home* at an individual level rather than across the population. 19% of the observations for part-timers indicate reduced working hours due to childcare. For full-time employees, this is a lot less, with 2.3%. From the people that reduce their hours worked to care for children, part-timers on average reduce their hours with 1.8 hours, while full-timers reduce their hours on average with about 10 minutes.

In Appendix A.1 a more substantive table is provided with summary statistics of descriptive variables like gender and age as well as control variables. This information can be illustrative to the means from Table 3, Table 4 and Table 5. Overall, individuals who have a partner mostly live with them. On average, individuals have one child. People are mostly very satisfied with their working hours, and score it on average 7.5. Notice that men are on average more in the full-time group, while women are more present in the part-time group. In the part-time group, individuals on average take care of more children. Although part-timers self-report slightly higher, *Household Division Index* and *Care Division Index* do not differ much between full-time and part-time employees. This means both groups self-report similar task divisions. This means that full-timers as well as part-timers experience the same care demands. The care division index is on average only 1, on a scale from 0-24. This can be explained through the large amount of individuals that do not have children living at home, and thus not experience this type of care, see Appendix A.3.

### 4.3.1 Employment Variables

Figure 3 shows the mean hours employed by full-time status over the years. This figure shows the trend in employment contracts over the years. It becomes clear that individuals initially marked as part-time employees (full-time Status 0), show a small increase in their employment hours. For employees initially marked full-timer, contracts seem to slightly decrease in average amount of hours, but remain well in the full-time range. The expectation is that more WFH would increase the amount of hours worked. This figure suggests this for part-time employees.

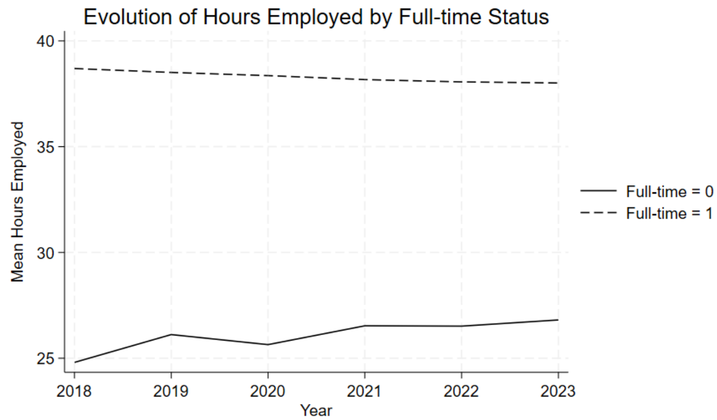



*Figure 3:* *Hours Employed by Year and Full-time Status.* This figure projects the trend of mean hours employed for individuals with part-time status (Full-time Status = 0) and full-time status (Full-time Status = 1) across 2018-2023. The x-axis indicates the year, and the y-axis represents the mean amount of hours individuals from a group are employed for on average

Figure 4 shows the mean amount of average hours worked per week by full-time status. This figure suggests a dip in actual hours worked for full-time employees during COVID. For part-time employees, theere is a slight increase.

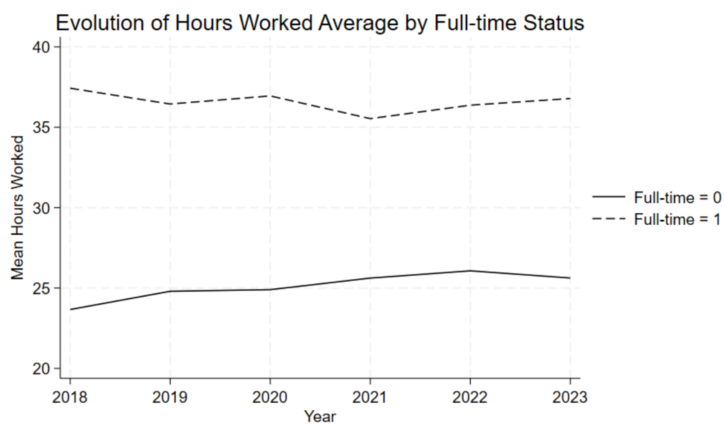
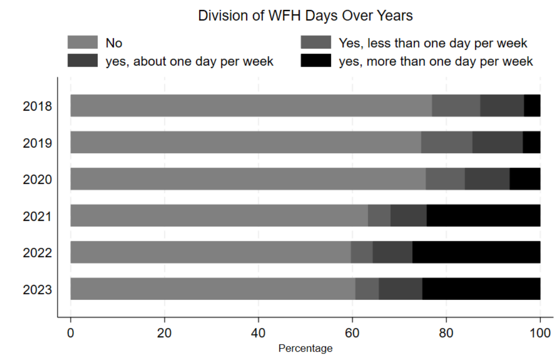


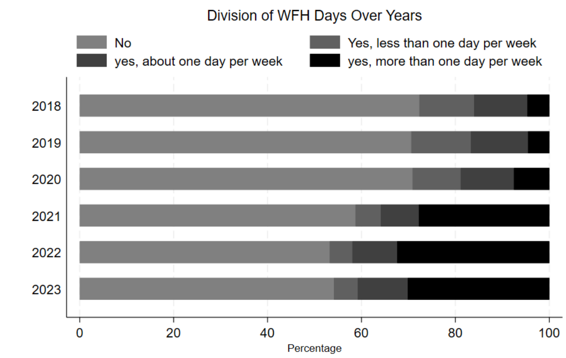

*Figure 4:* *Hours Worked per Year and Full-time Status.* This figure projects the trend of mean hours employed for individuals classified as part-time (Full-time Status = 0) and full-time (Full-time Status = 1) across 2018-2023. The x-axis indicates the year, and the y-axis represents the mean amount of hours individuals from a group are employed for on average.

Figure 5 illustrates the trend of *Days WFH* over the years. Since it is an ordinal variable, interpreting the mean does not provide accurate insights into the amount of WFH employees have, and thus, interpreting the distribution provides more information. This figure suggests that Pre-COVID, most employees did not work from home. As 2020 might still project the average hours worked based on the Pre-COVID period, this trend is still present here. In the COVID 2 and Post-COVID period, the share of employees working from home increases. Especially the amount of employees working more than one day from home increased substantially, while the amount of employees working half a day from home decreased. This is in line with increased WFH during COVID, and the expectation of WFH staying up after. Full-timers keep similar levels of WFH during and after the pandemic, while part-time employees decrease their WFH slightly, but remain significantly above their Pre-COVID levels.

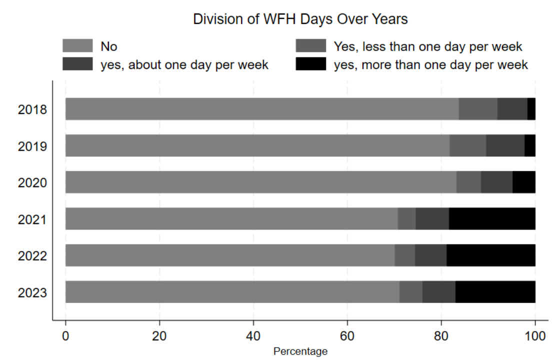
Appendix A.4.2 illustrates that the mean employment of men remains around 37 hours of employment, while women report a mean around 30 hours. Average hours worked is more volatile for both men and women, although both report on average to work less than their employment.




*(a)* WFH Days Over Years




*(b)* WFH Days Over Years (full-time)




*(c)* WFH Days Over Years (part-time)

*Figure 5: WFH Days over 2018-2023.* The figures present data on work-from-home (WFH) days, split by full-time and part-time status, and show trends over the years. The subfigures illustrate the changes and distributions of WFH days for different employment statuses.

The results in Figure 5 do not seem to match the results from CBS (2024b). This could possibly be explained through the way questions were asked. The CBS classifies all workers that work between 0 and half of the amount of hours they are employed for, as 'sometimes working from home'. This might include all WFH time, as well as flexible WFH day, or occasional hours. As for the LISS panel, the question regarding *Days WFH*, "Do you have a (partial) "working-from-home day"?", might get more answers pointing at contractual WFH. This means that where LISS records a large group of employees without *Days WFH*, CBS might be classifying part of that as sometimes working from home, on a flexible basis. This difference might be the difference between half of the working population having some work from home time and not.

Another interesting pre-analysis statistic is the amount of changes for the variable *Hours Worked Less Because of Responsibilities at Home* and *Hours Worked Less Because of Care for Children*. The amount of changes can give a first indication of whether individuals over time started working less or more, taking into account their home and care responsibilities. Outcomes can be found in Appendix A.5. It shows that there are minimal changes based on home tasks, suggesting that working from home may not have a strong effect on balancing home responsibilities with work. There were only two changes reported, which were two observations were the individual changed from working part-time to take care of the household, to full-time employment. There were more changes in regard to childcare responsibilities. Given the relatively low number of parents with children living at home in the dataset, this change is noteworthy, see Appendix A.3. Specifically, changes in working less due to childcare responsibilities show a small peak in 2021, coded as COVID 2. Changes do not show large effects. However, in total there seems to be a larger effect for childcare, suggesting working from home makes it easier to take care of children during work, allowing for more working hours. Another reason why this second analysis might show larger changes, is that a change happens if someone works less or more in general, while for housework a change only happens when someone starts to work more or less than 36 hours specifically.

### 4.3.2 Further Summary Statistics

On average, individuals are very satisfied with their working hours. Over the years, this has not changed a lot. This is not a surprising outcome, because individuals who are not satisfied might make a change, causing them to increase their satisfaction. See Appendix A.6

For sectors, I find that over time, the amount of respondents per sector do not change a lot, although sectors 'Healthcare and welfare' and 'Retail trade' and 'Industrial production' show some slightly larger changes. There are large differences in observations between sectors. The largest sector is "other", which does not provide a lot of information. See Appendix A.7.

## 4.4 Analytical Framework

### 4.4.1 Panel Data

Panel data follows multiple individuals over multiple periods. In this study, 3,226 individuals were tracked over six time periods. Compared to cross-sectional or time series data, panel data offers several benefits: it encompasses a larger dataset with more variability and less collinearity, provides more informative results, and controls for individual heterogeneity (Baltagi and Song, 2006). Additionally, panel data enables the discovery of effects that might not be detectable within a single period, allowing for the investigation of more complex questions.

In balanced panels, all individuals are observed over all time periods. However, for a number of reasons, it may be the case that some individuals are missing in some time periods. When the dataset does not have observations for all individuals in all periods, we speak of an unbalanced panel. If individuals drop out of the dataset on a non-random basis, this can lead to measurement errors and bias. In this research, restricting the dataset to individuals who responded in all time periods, reduces the number of observations per period from approximately 1,500 to 308. While a balanced panel has its advantages, this results in insufficient individuals to track over time. An unbalanced panel is allows for a larger sample size, which allows for more information to be used in the regression. Therefore, I choose to use the unbalanced panel. STATA automatically handles unbalanced data when using its fixed effects regression functions (STATA, 2023). This means that I will not lose individuals over incomplete time series, and STATA calculates the results keeping this in mind.

### 4.4.2 Fixed Effects Regression

According to the Fixed Effects model (FE), there is one true effect that underlines each study, and that all outcomes that differ from this are caused by sampling errors (Borenstein et al., 2010). Using a FE model, allows me to control for unobserved heterogeneity, because the fixed effects account for characteristics that are time-invariant (Greene, 2020). Using this method, I can look at within-individual changes over time, and see what the effect of WFH on work hours is. Also, adding time fixed effects by controling for the different COVID periods, allows me to control for period-specific shocks, and make a distinction between the different periods.

There are a few assumptions on which the FE model is built (Christoph Hanck, 2024). The first is 'time-invariant unobserved heterogeneity'. This means that individual-specific effects are constant over time. The FE model then controls for the fact that this can be correlated with the independent and/or dependent variables. This can be tested with the Hausman Test. Significant results suggest the FE model to be more appropriate. The second is no multicollinearity, which means that the explanatory variables may not be perfectly correlated with each other. This can be tested with the Variance Inflation Factor test (VIF). The mean of the outcomes should be under 10. The third assumption is homoskedasticity. This means that all error terms in the regression have the same variance over time and across individuals. Homoskedasticity ensures that the variance of the error terms is constant and does not depend on the values of the independent variables. To address this assumption, I use standard errors. Using robust standard errors helps to ensure that there is no heteroskedasticity, meaning that the potential issue of varying error term variance is accounted for and corrected, thereby providing more reliable and accurate estimates in the regression analysis. Lastly, there should be no serial correlation, meaning that the error terms for the different periods should not be correlated with each other. See Appendix B for the results to the tests. The Hausman tests points at the FE model, and no multicollinearity and homoskedasticity are accounted for. Finally, for serial correlation, I regressed the residuals. I found a significant p-value (at the 0.01% level), and a negative coefficient. This points to serial correlation where positive results are followed by negative results and vice versa. I solved this by using robust standard errors clustered on an individual level.

## 4.5 Research Model

For the analysis, I use a Fixed Effects OLS model with the panel data obtained from LISS. Fixed effects analysis allows me to account for unobserved heterogeneity that is constant over time. I control for both individual fixed effects and time fixed effects. By controlling for individuals fixed effects, I control for characteristics of the individual that do not change over time. In the context of this study, I control for time fixed effects by controlling for COVID Periods. The different COVID periods to account for variations in effects across these periods, which allows me to address the different shocks and trends, and to make statements about each period.

The analysis is split into two in order to account for differences between full-time and part-time employees. I do this, because I assume that part-time workers benefit differently from a day of WFH than individuals who work full-time. This is based on the assumption that part-time workers have more time left in their week for unpaid work, comprised of home responsibilities and possibly childcare responsibilities. Individuals who work part-time might have less additional benefit from a day working from home than individuals who do work full-time. Thus, it is beneficial to split the sample into these two groups, because their effects are expected to be different. For Hypothesis 2, I did not do this, I looked at the full sample and separately the part-time sample. The reason for this was that a separate analysis for full-time employees was not possible due to omitted variables. The selection for full-time employees was based on the criterion of working more than 36 hours in 2018 or 2019, resulting in too little variation. To test the first hypothesis, I look at the effect of the amount of (part-)days worked from home on the amount of hours the employee actually works per week. The independent variable is (part-)days worked from home per week, the dependent variable is average hours worked per week. The interaction term indicates how the effect of WFH varies across different COVID periods. The basic model is thus as follows:

$$\begin{aligned}\text{Hours Worked}_{i,t} = \beta_0 + \beta_1 \text{WFH Day}_{i,t} + \beta_2 \text{COVIDPeriod}_t \\ + \beta_3 (\text{WFH Day}_{i,t} \times \text{COVIDPeriod}_t) + \alpha_i + \epsilon_{i,t}\end{aligned} \tag{1}$$

Hypothesis 2 is tested through the regression of *Days WFH* on *Working less for Home*:

$$\begin{aligned}\text{Working Less for Home}_{i,t} = \beta_0 + \beta_1 \text{WFH Day}_{i,t} + \beta_2 \text{COVIDPeriod}_t \\ + \beta_3 (\text{WFH hours}_{i,t} \times \text{COVIDPeriod}_t) + \alpha_i + \epsilon_{i,t}\end{aligned} \tag{2}$$

I test Hypothesis 3 through the regression of (part-)days worked from home on *Working Less for Children*:

$$\begin{aligned}\text{Working Less for Children}_{i,t} = \beta_0 + \beta_1 \text{WFH Day}_{i,t} + \beta_2 \text{COVIDPeriod}_t \\ + \beta_3 (\text{WFH hours}_{i,t} \times \text{COVIDPeriod}_t) + \alpha_i + \epsilon_{i,t}\end{aligned} \tag{3}$$

As discussed previously, *COVIDPeriod* and the interaction term of *WFH Day* and *COVIDPeriod* allow me to look at the effect of WFH during the differentiated periods. It allows me to make a difference between periods where children were more at home, and employees and their employers were not yet accustomed to WFH and periods in which this was different.

To all regressions, I add the same control variables: *Age*, *Live Together*, *Children 0-4*, *Chil-*

*dren 5-11*, *Children 12+*, *Part-Days Childcare*, *Commute time*, *Sector of Employment*, *Satisfaction Workhours*, *Household Division Index* and *Care Division Index*.

# 5 Results and Analysis

This section provides the results to the analysis of the previously discussed data and methodology. I aim to show the findings and interpret them, in order to come to an answer to the previously posed questions and hypotheses. Tables in this section only present the main variables, tables with controls are presented in Appendix C.

## 5.1 Hypothesis 1

Table 6 shows the results of the fixed effects regression analysis for Hypothesis 1. Analysis shows that there is a significant positive effect for full-time employees that work from home for less than one day. Further results, although not significant, indicate that the more WFH time is taken, the weaker the effect is. This holds for both full-time employees, and for part-time employees, experiencing a negative effect. The effect for part-timers is in line with predictions of reduced working hours for women.

Looking at the time periods, significant effects are found for full-time employees, in the model without controls. For full-time employees, the results suggest that the average amount of hours worked decreases in all periods compared to Pre-COVID. Part-time employees appear to have increased their hours worked over time, in line with adapting to WFH. When interacting *Days WFH* and *COVIDPeriod*, no significant results are found. Relatively large standard errors (SE) make it difficult to draw strong conclusions. The large SE are probably due to the large amount of subgroups.

The coefficients on the control variables reveal interesting effects for different subgroups. Full-timers living together with a partner tend to work less. This might be because of distractions at home. Although not significant, results suggest that full-timers with children increase their hours worked, increasing in the age of the children. This is in line with the expectation that young children distract their parents and increase difficulties working from home, having to decrease hours worked. Both full-time and part-time employees decrease hours worked with increasing *Household Division Index*. For part-timers, I also find this for the *Care Division Index*. Hours worked seem to be correlated with work hour satisfaction for both groups, implying that individuals who are more content with their hours, work fewer hours on average. Job sectors do not render significant results.

The first hypothesis, *H1: Employees working more time from home per week, end up working more hours per week* cannot be confirmed. The results suggest that *Hours Worked* increases with WFH for full-timers, for part-timers the opposite has been found. This suggests that part-timers might be more distracted when at home, possibly by taking up more unpaid responsibilities.

**Table 6.** *FE Regression Results: Impact of WFH Days on Hours Worked Across COVID Periods*

| | **Hours Worked** | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | 2.799* | 3.255* | 0.117 | -0.091 |
| | (1.351) | (1.341) | (1.526) | (1.550) |
| 1 day | 1.547 | 2.000 | -2.268 | -2.404 |
| | (1.792) | (1.735) | (1.651) | (1.656) |
| >1 day | 1.533 | 1.258 | -0.641 | -0.816 |
| | (1.901) | (1.939) | (3.145) | (3.233) |
| **COVID Period** | | | | |
| COVID 1 | -0.630 | 0.271 | 0.447 | 0.749 |
| | (0.687) | (1.258) | (0.483) | (1.254) |
| COVID 2 | -2.670** | -0.912 | 0.618 | 1.425 |
| | (0.727) | (1.780) | (0.598) | (2.014) |
| Post-COVID | -2.217** | -0.021 | 0.819 | 1.753 |
| | (0.640) | (2.379) | (0.594) | (2.656) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | -2.066 | -2.297 | -3.869 | -3.593 |
| | (1.857) | (1.840) | (2.384) | (2.432) |
| <1 day * COVID 2 | -1.572 | -2.192 | 2.382 | 2.131 |
| | (2.590) | (2.613) | (2.092) | (2.142) |
| <1 day * Post-COVID | -1.709 | -2.373 | -2.677 | -2.690 |
| | (2.309) | (2.317) | (2.304) | (2.355) |
| 1 day * COVID 1 | 1.712 | 1.477 | 1.376 | 1.046 |
| | (2.212) | (2.213) | (2.065) | (1.892) |
| 1 day * COVID 2 | 3.072 | 2.906 | -0.191 | -0.005 |
| | (2.645) | (2.596) | (1.937) | (1.921) |
| 1 day * Post-COVID | 1.479 | 0.937 | 1.274 | 1.404 |
| | (2.148) | (2.088) | (1.820) | (1.850) |
| >1 day * COVID 1 | -0.790 | -0.519 | 2.682 | 2.931 |
| | (2.428) | (2.451) | (3.182) | (3.234) |
| >1 day * COVID 2 | 0.968 | 1.353 | 1.057 | 1.191 |
| | (2.004) | (2.019) | (3.172) | (3.239) |
| >1 day * Post-COVID | 0.109 | 0.764 | -0.123 | 0.266 |
| | (1.898) | (1.921) | (3.120) | (3.242) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 37.131** | 72.912** | 24.814** | 43.963 |
| | (0.419) | (28.024) | (0.330) | (30.338) |
| **Number of observations** | 5307 | 5307 | 3314 | 3314 |

*Note.* This table provides the outcomes for regression of WFH Days on Hours Worked. WFH stands for 'Work From Home'. Columns 1 and 2 present the outcomes for employees labeled full-time, columns 3 and 4 present the outcomes for employees labeled part-time. Standard errors are in parentheses. * $p < .01$, ** $p < .05$

## 5.2 Hypothesis 2

Table 7 presents the results of the fixed effects regression analysis for Hypothesis 2. The results show very small effects, and only a few statistically significant outcomes in the model without controls. Overall, coefficients are close to zero, suggesting that there is no strong relationship between *Days WFH* and *Working Less for Home*. This is not unexpected, as Appendix A.5 already showed that not many observations showed changes from and to part-time for this reason. Besides this, Appendix A.2 shows that not many people changed from full-time to part-time at all. *Days WFH*, thus suggests very little impact from WFH on the chances someone works less because of responsibilities at home.

I find significant results for the different periods of COVID in the models without controls. All signify a negative effect compared to Pre-COVID. This suggests that the chances of working part-time to manage household duties decreased during these periods. For part-timers, this effect was also found. I observed similar effects for part-timers, where the likelihood of reducing work hours decreased significantly without controls, but this effect disappeared once controls were added. This might be explained by the fact that with the small amount of observations, and the small groups, it is hard to find significant effects.

I find positive effects of WFH during the different COVID periods for both the full sample and for part-time employees. This indicates that in all periods, chances of working less to take care of the home increase when WFH. Even still, effects are very weak.

Further, age seems to reduce the likelihood of working less to take care of the household. I expected a higher *Household Division Index* to increase the effect of *Days WFH* on *Working Less for Home*. For both the full sample and for part-timers, there is no significant evidence to support this. I also hypothesized that over time, a larger effect would occur. With the weakness of the effect and lack of significant results, I cannot confirm this. Finally, I expected that part-timers would experience less effect during COVID, and larger after. I did not find evidence to support this. Job sectors do not render significant results.

The second hypothesis was: *H2: Employees who increase their WFH, decrease their chances of having to work less to take care of the household.* This hypothesis cannot be supported based on this analysis. Very small effects have been found, but not significant. With the low intercept in combination with the small coefficients, chances of WFH having a noticeable impact on working less for this reason are already quite small. These findings do not align with the predictions according to the models.

**Table 7.** *FE Regression Results: Impact of WFH Days on Working Less Because of Home Across COVID Periods*

| Working Less Because of Responsibilities at Home | | | | |
|---|---|---|---|---|
| | Full sample | Full sample | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | -0.003 | -0.003 | -0.007 | -0.009 |
| | (0.002) | (0.002) | (0.004) | (0.004) |
| 1 day | -0.002* | -0.002 | -0.006* | -0.006 |
| | (0.001) | (0.001) | (0.003) | (0.004) |
| >1 day | -0.002* | -0.001 | -0.005* | -0.001 |
| | (0.001) | (0.001) | (0.002) | (0.005) |
| **COVID Period** | | | | |
| COVID 1 | -0.002* | 0.003 | -0.006* | 0.009 |
| | (0.001) | (0.002) | (0.003) | (0.005) |
| COVID 2 | -0.004* | 0.005 | -0.010* | 0.015 |
| | (0.002) | (0.003) | (0.004) | (0.009) |
| Post-COVID | -0.004* | 0.008 | -0.011* | 0.022 |
| | (0.002) | (0.004) | (0.005) | (0.012) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | 0.000 | 0.001 | -0.004 | -0.003 |
| | (0.002) | (0.002) | (0.009) | (0.007) |
| <1 day * COVID 2 | 0.004* | 0.004* | 0.009* | 0.005 |
| | (0.002) | (0.002) | (0.004) | (0.005) |
| <1 day * Post-COVID | 0.004* | 0.004* | 0.010* | 0.009* |
| | (0.002) | (0.002) | (0.005) | (0.004) |
| 1 day * COVID 1 | 0.003* | 0.003* | 0.007* | 0.004 |
| | (0.001) | (0.001) | (0.003) | (0.003) |
| 1 day * COVID 2 | 0.004* | 0.003 | 0.010* | 0.009 |
| | (0.002) | (0.002) | (0.005) | (0.005) |
| 1 day * Post-COVID | 0.004* | 0.004 | 0.011* | 0.011 |
| | (0.002) | (0.002) | (0.005) | (0.006) |
| >1 day * COVID 1 | 0.003* | 0.002 | 0.006* | 0.006 |
| | (0.001) | (0.001) | (0.003) | (0.005) |
| >1 day * COVID 2 | 0.004* | 0.003* | 0.009* | 0.005 |
| | (0.002) | (0.001) | (0.004) | (0.005) |
| >1 day * Post-COVID | 0.004* | 0.003 | 0.010* | 0.005 |
| | (0.002) | (0.002) | (0.005) | (0.006) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.003** | 0.128* | 0.009** | 0.359* |
| | (0.001) | (0.056) | (0.003) | (0.160) |
| **Number of observations** | 8621 | 8621 | 3314 | 3314 |

*Note:* ** p<.01, * p<.05

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on working less because of home responsibilities across different COVID periods. Columns 1 and 2 show the results for the full sample, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * p < 0.01, ** p < 0.05.

### 5.3 Hypothesis 3a

Table 8 shows the results of the fixed effects regression analysis for Hypothesis 3a. Although again a lot of the results are not significant, some indications to an effect can be given. Overall, coefficients are close to zero, suggesting no strong relationship. Both full-timers and part-timers do not show a clear trend of the effect WFH on the chance of working less to take care of children.

For all COVID periods, I find significant effects in the model without controls, and not significant results in the model with controls. The direction seems to change when controls are added. Specifically, the results without controls suggest that for full-timers, the chances of reducing work hours increased over time, while for part-timers, these chances decreased—contradicting the prediction that effects would be smaller during COVID compared to before and after. [1].

When *Days WFH* and *COVIDPeriod* are interacted, part-timers working more than one day from home in COVID 1, increase the chance of having to reduce their hours to take care of children.

For part-timers, age decreases the chance of having to reduce work hours to take care of children. Although children at different ages are controlled for, this might give an indication that older people have less care responsibilities to their children. However, it might also suggest that older people are more stable in their career and can opt for other care options than staying home. For full-timers, having children in any age category increases the likelihood of reducing work hours, though this effect diminishes as children get older. The coefficient on *Care Division Index* is not statistically significant for either full-timers or part-timers. Results do however suggest that higher indexes go together with higher chances of having to stay home. Part-timers working in healthcare increase their chances of decreasing work hours to take care of children.

Hypothesis 3a, *Employees who increase their WFH, decrease their chances of having to work less to take care of children*, can only be confirmed for part-time employees working from home for more than a day during COVID 1. Besides, as expected, result size is mostly larger for part-time employees, although it not always decreases their chances to reduce their hours.

[1] Remember that COVID 1 mostly records what happened over the year 2019-2020, as respondents record their averages of the year in April and May. This means that in April 2020, mostly averages up until COVID would be recorded

**Table 8.** *FE Regression Results: Impact of WFH Days on Working Less For Children Across COVID Periods*

| Working less for Childcare Responsibilities | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | -0.001 | -0.011 | 0.033 | 0.012 |
| | (0.014) | (0.014) | (0.063) | (0.063) |
| 1 day | 0.017 | 0.004 | 0.044 | 0.041 |
| | (0.014) | (0.014) | (0.057) | (0.056) |
| >1 day | -0.010 | -0.013 | -0.127 | -0.137 |
| | (0.022) | (0.016) | (0.071) | (0.076) |
| **COVID Period** | | | | |
| COVID 1 | 0.013* | -0.004 | -0.096** | -0.002 |
| | (0.007) | (0.011) | (0.018) | (0.035) |
| COVID 2 | 0.017* | -0.018 | -0.094** | 0.046 |
| | (0.008) | (0.016) | (0.021) | (0.053) |
| Post-COVID | 0.018 | -0.029 | -0.094** | 0.094 |
| | (0.009) | (0.021) | (0.021) | (0.071) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | 0.010 | 0.009 | 0.076 | 0.061 |
| | (0.016) | (0.014) | (0.092) | (0.091) |
| <1 day * COVID 2 | 0.046 | 0.052* | -0.111 | -0.104 |
| | (0.027) | (0.025) | (0.107) | (0.103) |
| <1 day * Post-COVID | 0.014 | 0.033 | -0.115 | -0.119 |
| | (0.017) | (0.017) | (0.115) | (0.118) |
| 1 day * COVID 1 | -0.014 | -0.010 | 0.012 | -0.004 |
| | (0.015) | (0.015) | (0.066) | (0.064) |
| 1 day * COVID 2 | -0.007 | -0.008 | -0.000 | -0.008 |
| | (0.020) | (0.020) | (0.063) | (0.061) |
| 1 day * Post-COVID | -0.018 | -0.003 | -0.084 | -0.092 |
| | (0.017) | (0.017) | (0.079) | (0.078) |
| >1 day * COVID 1 | 0.023 | 0.020 | 0.192** | 0.179* |
| | (0.027) | (0.025) | (0.070) | (0.071) |
| >1 day * COVID 2 | 0.008 | 0.011 | 0.098 | 0.113 |
| | (0.021) | (0.017) | (0.074) | (0.077) |
| >1 day * Post-COVID | 0.017 | 0.020 | 0.106 | 0.118 |
| | (0.020) | (0.016) | (0.072) | (0.078) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.009* | -0.492 | 0.254** | 2.303** |
| | (0.005) | (0.262) | (0.012) | (0.852) |
| **Number of observations** | 5307 | 5307 | 3314 | 3314 |

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on working less because of childcare responsibilities across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.

## 5.4 Hypothesis 3b

Table 9 presents the results of the fixed effects regression analysis for Hypothesis 3b. In this section, I examine how COVID periods and the amount of WFH influenced the extent to which people who reduced their hours to care for children actually did so. Although many results are not statistically significant, there are some indications of potential effects. Relatively large standard errors (SE) occur in these results, probably due to the large amount of subgroups. The effect sizes are slightly larger than in the previous section, which makes sense, as individuals in this group have already adjusted their hours for childcare and may therefore be more heavily impacted by changes in their work environment. For part-timers, increasing WFH slightly reduces the number of hours cut for childcare, though the effect is small—working more than a day from home reduces their reduction by only an hour. Full-timers, on the other hand, might reduce their cutback if they work less than a day from home.

For all COVID periods, I find significant effects in the model without controls, and not significant results in the model with controls. The models without controls suggest that full-timers would increase their reduction and part-timers would decrease it. This might illustrate full-timers being more distracted when they work from home, while part-timers can balance work and childcare better, as described by (Beauregard et al., 2019). During COVID 1 and post-COVID, part-timers with more than 1 WFH day, increase their reduction. This is opposite to SET, which predicts the opposite to happen.

For full-timers, age decreases the extent of work hour reduction to take care of children. Further, both full-timers and part-timers experience effects of children, with a decreasing impact as children age. For full-timers this effect is larger as well as significant, while for part-timers, they were smaller and not significant. The coefficient on the *Childcare Division Index* is not significant, but points at a positive effect. Job sectors do not render significant results.

The final hypothesis was: *Employees who increase their WFH, can reduce the number of hours they work less to take care of children.* This hypothesis can only be confirmed outside of COVID, for part-time employees working from home for more than a day.

**Table 9.** *FE Regression Results: Impact of WFH Days on Hours Worked Less For Children Across COVID Periods*

| **Hours less for Childcare Responsibilities** | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | 0.147 | 0.055 | 0.205 | 0.024 |
| | (0.102) | (0.102) | (0.917) | (0.928) |
| 1 day | 0.217 | 0.105 | -0.363 | -0.356 |
| | (0.118) | (0.114) | (0.516) | (0.513) |
| >1 day | -0.017 | -0.028 | -1.250** | -1.290** |
| | (0.171) | (0.122) | (0.447) | (0.488) |
| **COVID Period** | | | | |
| COVID 1 | 0.179* | -0.011 | -1.086** | -0.194 |
| | (0.072) | (0.103) | (0.219) | (0.439) |
| COVID 2 | 0.200** | -0.161 | -1.028** | 0.258 |
| | (0.068) | (0.133) | (0.255) | (0.678) |
| Post-COVID | 0.216** | -0.275 | -1.293** | 0.464 |
| | (0.081) | (0.173) | (0.265) | (0.905) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | -0.046 | -0.066 | 0.336 | 0.192 |
| | (0.112) | (0.102) | (1.065) | (1.050) |
| <1 day * COVID 2 | 0.277 | 0.331 | -0.975 | -0.856 |
| | (0.223) | (0.244) | (1.020) | (1.008) |
| <1 day * Post-COVID | -0.004 | 0.173 | -0.104 | -0.221 |
| | (0.123) | (0.138) | (1.157) | (1.145) |
| 1 day * COVID 1 | -0.155 | -0.133 | 0.781 | 0.598 |
| | (0.123) | (0.125) | (0.526) | (0.531) |
| 1 day * COVID 2 | -0.054 | -0.069 | 1.606 | 1.460 |
| | (0.219) | (0.213) | (0.938) | (0.912) |
| 1 day * Post-COVID | -0.295* | -0.160 | 0.059 | -0.158 |
| | (0.118) | (0.115) | (0.802) | (0.814) |
| >1 day * COVID 1 | 0.036 | 0.007 | 1.486** | 1.164* |
| | (0.184) | (0.155) | (0.518) | (0.537) |
| >1 day * COVID 2 | 0.013 | 0.029 | 0.909 | 1.036 |
| | (0.171) | (0.127) | (0.529) | (0.559) |
| >1 day * Post-COVID | 0.036 | 0.055 | 1.294** | 1.351* |
| | (0.164) | (0.122) | (0.501) | (0.561) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.010 | -5.321* | 2.667** | 19.101 |
| | (0.046) | (2.166) | (0.148) | (11.360) |
| **Number of observations** | 5307 | 5307 | 3314 | 3314 |

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on the number of hours worked less because of childcare responsibilities across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.

## 5.5 Additional Analysis

In the additional analysis, I focus on *Hours WFH* instead of *Days WFH*. The underlying mechanism flexible WFH hours can introduce flexibility into the employee's work-life. As seen in the literature section previously, flexibility can increase productivity. As I only have data for this analysis for 2020 onwards, I compare the outcomes to this analysis with the results from the panel with *Days WFH*, but done from 2020 onwards as well, to check for robustness. The summarized results of this analysis are provided in Appendix D. Note that hypothesis 2 is not included in the Appendix. As no changes in the dependent variable were recorded from 2020 onward, no analysis could be done for this hypothesis under the conditions of this additional analysis.

Table 23 presents the results of the analysis for hypothesis 1. Although there are no significant coefficients for *Hours WFH*, results suggest a small, but positive effect of *Hours WFH* on *Hours Worked*. For full-timers, COVID 2 and Post-COVID indicate a negative effect on the amount of hours worked, compared to COVID 1. Post-COVID was expected to have positive effects, because of SET as well as people having been able to adjust. For part-timers, this effect is not significant and positive. Interacted, no significant results are found. Again, the hypothesis is not supported based on these results, although outside of COVID, results are illustrative for a positive effect. Note that the constant for full-timers with controls is largely negative, as well as the coefficients for *COVIDPeriod*. This is offset by the large coefficients of the control variables.

In the model looking at *Working Less for Children* presented in Table 24, again, effects that are close to zero and not significant are found. However, with the independent variable being hours instead of days, smaller effects are expected. With these outcomes, the hypothesis is not supported.

Finally, in the model looking at the amount of hours individuals work less because of childcare, presented in Table 25 again, no significant results are found. The outcomes, although not significant, suggest a very small negative effect on the amount of reduced hours.

Possibly, as the observations to these analyses are more limited, this decreases the probability of finding significant results.

### 5.5.1 Robustness Check

To check whether this additional analysis is robust, I compare the outcomes to the outcomes of the main analysis, done for 2020-2023. The summarized results to this check can be found in Appendix E.

The analysis of *Days WFH* and *Hours Worked* can give an indication of the relationship between the amount of WFH time and *Hours Worked*, where *Hours WFH* might give a more general image. Results found in the additional analysis do find similarities in the effect with the *Days WFH* analysis. However, as the background of the question is different, it is hard to compare the two outcomes with each other. Both results indicate a positive effect of WFH time on *Hours Worked* for full-time employees, and a negative effect for part-time employees. The results for hypothesis 3a are very small and not significant for both situations, and for 3b this is the case as well.

Similarities can be found comparing the period-effects in all analyses. The fact that the indicators for time-period show the same effect gives a positive indication that the results for this variable are robust. That the results of *Hours WFH* and *Days WFH* suggest different sizes of effect and sometimes direction, might support the idea that they are built off different ideas. The hour variable might then show the effects of flexibility, while the day variable shows the ability to plan around the fact that you work from home.

# 6 Conclusion

In this research, I looked into the effects of working from home (WFH) on work effort. Because the amount of WFH increased rapidly due to it becoming mandatory during the COVID-19 pandemic, and due to an existing WFH trend, WFH became more normal after the pandemic. To find out what the effects are in terms of the amount of time individuals spent working due to this change in workplace, I looked into the following research question:

*"How has the shift to teleworking affected the work hours of Dutch employees, specifically in terms of reductions below 36 weekly hours due to household and childcare responsibilities, from 2018 to 2023, and how do these changes differ between parents and non-parents, with different responsibilities and among various job sectors?"*

As WFH becomes a standard mode of operation, it is interesting for employers to know what the mechanisms are behind employees WLB and if this could increase work effort and productivity. This can help employers to develop strategies supporting employees in maintaining WLB while also ensuring work hours are completed.

Fixed effects regression allowed me to look at a panel of around 8.500 observations, and make conclusions based on the changes within entities over the measurement period, which was between 2018-2023. For this, I made use of 2 longitudinal LISS Panel datasets. Fixed effects regressions removes the effects of an individuals' characteristics that do not change over time, to maintain only the true effect. I only look at individuals that are employed, and are between the ages of 15 and 75 years old. I split the sample in full-time and part-time employees, based on their first observation. This allows me to differentiate between the expected differing effects between the two. To the regressions, I also added a period-variable, *COVIDPeriod*, that provides information about the time frame. Controlling for the periods in this case comes instead of year fixed effects.

According to the Job Characteristics Model and the Job-Demands Resources model, people need certain resources and job characteristics to be productive at their jobs. The Conservation of Resources Theory predicts that they will try to maintain the resources they have, to succeed in new and threatening situations, like the COVID-19 pandemic. Finally, the Social Exchange Theory predicts that when resources like flexibility are provided, employees feel the need to return the favor and work harder for their boss. This, together with different factors that play a role in work- and home-life, I made the following predictions:

1. Employees working more time from home per week, end up working more hours per week.

2. Employees who increase their WFH, decrease their chances of having to work less to take care of the household.

3a. Employees who increase their WFH, decrease their chances of having to work less to take care of children.

3b. Employees who increase their WFH, can reduce the number of hours they work less to take care of children.

Hypothesis 1 is not supported by the results. However, outcomes suggest that outside of COVID, full-timers increased their work hours, and part-timers decreased it. During COVID, results do not point to a clear trend. Hypothesis 2 is also not supported, and only the suggestion of a very small effect size were found. The third hypothesis is not supported either, for both 3a and 3b. However, outside of COVID, part-time employees working more than one day from home might increase the chance of not having to reduce work hours, as well as having to reduce with fewer hours. Because the results were hard to interpret, linking with the theory is difficult. However, some suggestive evidence to both support and reject SET in the Post-COVID period was found.

To answer the main research question, shifting to WFH had different impacts on Dutch individuals. Although none of the hypotheses rendered significant results, there are some indications to be made as to the size and direction of the effects. In general, results seem to illustrate that full-timers and part-timers do not experience the same effects. Children reduce the time their parents work, and the division of tasks may play a role in the effect size of WFH. Men are more often full-timers than women, who work more part-time. Keeping this in mind when looking at the results, can give some indication of gendered effects. The various job types did not provide significant results.

Overall, the results indicate that while WFH has increased and that there are potential benefits, its impacts on work hours and responsibilities are complex and vary among different groups. Employers and policymakers should take a nuanced approach in crafting WFH policies, considering factors like gender, employment status (full-time vs. part-time), and parental responsibilities to effectively support their workforce.

# 7 Discussion

In this section, I will discuss the limitations of this research. Additionally, I will provide suggestions for improvement and further research.

## 7.1 Limitations

The first limitation of the research lies in the data source itself. The different core studies of the LISS Panel are collected each year during the same months. However, each core study is done in different months, and over two months. This means that I had to make certain assumptions about the data. Firstly, with the data being collected over a longer period of time, unexpected shocks or events can occur that change the way respondents fill in the different surveys in one year, potentially altering results. Second, combining data from different core studies means that the researcher must assume that the data from the one core study has not changed until the other core study was done, or that the average over the year is an accurate representation. For 2020 this potentially caused a problem, with one survey done before the lockdown of 15 march, and the other done after. Factors at work and home changed drastically between these surveys, introducing bias when assuming that both surveys indicate the same moment in time. Finally, with only one measurement moment per year, it is assumed that data is the same for the whole year. Aside from this, there is missing data, as well as individuals not responding to all periods, creating an unbalanced panel. Although STATA does account for this in its functions, having a balanced panel is more straightforward to work with.

An advantage of the LISS panel is that the questions barely change over time. This allows participants as well as researchers to use the same understanding of the question over time. However, if respondents do not understand the question well, and consistently fill them in wrongly, this can introduce bias. Another problem with survey data is possible recall bias. As mentioned, the surveys are distributed only once per year, and thus it is assumed that individuals can accurately recall how they should answer the question for the complete year. An example of this concerns the variable *Hours Worked*. According to the peak-end rule, respondents would be more likely to calculate this based on extremes, and what they have done recently, more than what accurately might have been the average.

Furthermore, in this research, some assumptions have been made based on the available data. The variable *Working Less for Home* includes only two very specific question from the survey, and limits the amount of worked less to 4 hours, or at least only asks if individuals decide to work less than 36 hours for this reason. Besides, a positive answer to the questions also depends on the specific 36-hour threshold. Further, the questions are not very clearly formulated, so it is plausible that respondents may have misunderstood the intent of the questions, or did not perceive themselves as fitting the intended category, despite being included in the parameters. Assuming that by including these two questions, all individuals working less to take care of the household are included, is not very robust.

A lot of the expected mechanism is based around the concept of productivity. Even though productivity is classically hard to quantify if not measured in produced units, average hours worked might still not be a reliable measurement unit. This is because an increase in hours worked could indicate a decline in productivity, requiring more time to complete tasks. Conversely, it could also reflect higher motivation and effort, or an increase in workload, leading to longer working hours. Thus, without a clear understanding of the underlying factors, average hours worked may not accurately capture changes in productivity. Changing this concept might make it easier to look for underlying mechanisms. Another aspect of this is that an increase in hours worked and better WLB does not speak to the quality of the work, nor to the quality of the housework or childcare.

In this research, I specifically study the different COVID periods, which have been defined earlier. Using this instead of years gives a more global impression of the time periods, than it would be by looking at years. Looking at separate years would give a better impression of separate periods and provide more robust results. However, it should be weighed up against reduced group size. One of the issues of the current research is that results are not significant which might be due to small groups. Making these groups half the size would probably decrease chances of finding effects even more. As there were now only two years included in the Post-COVID period, the group size effect will still weigh up against the robustness argument, but if the period would be increased for future research, it would be better to split it up. Note that I did split COVID 1 and 2 from each other. This was done because COVID 1 data might have partly represented pre-COVID data.

The question "Do you have a (partial) "working-at-home day"?" might introduce bias into the data, because it can be interpreted in different ways. It is unclear whether someone can contractually take WFH days, or if they have a standard day that they WFH, besides, having a partial WFH day can also be interpreted differently by different respondents. In this research, I assume that the question refers to an individual having a standard WFH day each week, around which they plan their life. However, not every respondent interpreting the question like this, might introduce bias through over- or underestimation, and it might influence the validity of the study. As it is the key question of the study, it is crucial that it is interpreted the same way by all individuals.

Further, I made assumptions by splitting the data for full-time and part-time employees. I classified individuals in the dataset based on their first observation. The assumption was that individuals entering the dataset as full-time or part-time would be included in those groups, and then behavioral changes within those groups could be visual. If individuals change their working status during the years 2020-2023, this could lead to misclassification and potentially to biases. However, As I have shown, groups maintained mostly stable. A possible risk with the transition table is that individuals that are only in the dataset for a short period, and not switch groups in that time, might influence the results. Maintaining stable group classifications based on Pre-COVID status, while conducting detailed subgroup analyses, allows me to balance consistency with the flexibility to capture changes in work patterns. Through this, I can make sure that the analysis is both meaningful and robust, and reflect the impact of WFH on WLB. For this reason, keeping stable groups provides reliable results, and aligns with the research objective to look for long term impact. Reclassifying individuals complicates interpretation. A possible risk of first observation classification is that there could be cohort effects. Individuals entering the dataset in a later stage could have already switched groups before entering the dataset, which is now unknown. This could cause misclassification bias, and could be solved in the future by using a dataset that allows for a balanced panel.

Results in this research might have been smaller than predicted by theory because theory is mostly based on office jobs. As this research included all types of sectors, and thus also a lot of observations in which people did not experience the mandatory WFH or are not able to work from home, this is reflected in the results.

To create the *Household Division Index* and the *Childcare Division Index*, I assumed the burden of all tasks falls on the single individual when they do not have a partner, not taking into account that they might actually be outsourcing. This might cause the index to be overestimated for single individuals. Besides, as it is based on a very subjective question, the index is based off how individuals perceive their division with their partners, more than how the actual division is. Although it is interesting to include the perceived division, because it might indicate mental pressure of tasks, looking at the objective division of tasks shows a more accurate distribution of tasks. This objective analysis can provide clearer insights into the actual workload and the efficiency of task distribution within households.

As most of the results were not significant, understanding why can reveal limitations and suggest directions for future research. Different groups might experience WFH and COVID-19 very differently. Despite applying a set of controls to the models, other variables might better explain the variance and increase significance. Measurement errors in self-reported data can also influence the observed relationships. Although the division of responsibilities was included in the model, it only addresses the relative pressures compared to a partner. An increase in tasks, with the same division, might complicate individuals' work situations, which the model does not measure. Including time periods in the models should partly control for the contextual factors of COVID-19. Finally, a large reason for not significant results, is small subgroups. This can also be confirmed through high SE's.

There are some concerns on the validity of the research. Firstly, using only age brackets to assume care needs for children, simplifies the interpretation of the results, but may fail to capture the complexity of childcare between these age groups as well as individuals and families. This means a lot of room is kept for interpretation of the coefficient and might lead to incomplete measurement of the concept. Second, The *Working Less for Home* variable might influence responses if differentially interpreted, like previously discussed.

My data did not allow me to look at the ability of the employer to facilitate the prompt switch to WFH during COVID. However, this might have greatly influenced the way individuals worked, their WLB and the amount of hours individuals worked. Not having this ability might influence the reliability of the results, because I assume that the change happened by going from the Pre-COVID period to the COVID 1 period. Another factor that might introduce bias is the lack of access to childcare during COVID, resulting in more children at home needing attention and increasing the risk and stress of job loss. However, with controlling for COVID-period, I assume a large general part of these period factors are included. Even though the effects of this are heterogeneous for individuals, it takes away some of this bias, because it allows for different interpretation across periods.

Assuming that there are no problems with heteroskedasticity, because I added robust standard errors is a large assumption, and likely not true in real life.

Finally, as this research is done with LISS Panel data, it most likely is replicable in the Dutch population, as they take a representative sample. However, the results might not be generalizable, because they are from a very specific time period with a big shock: COVID. Besides this, with different COVID-measures per country and company policies as well as overall culture being different between countries, also influence generalizability.

## 7.2 Recommendations

The independent variable, *Days WFH*, is unevenly categorized, meaning that the space between each category is not even. Although it might be tempting to assume that the category 'more than one day WFH' should be interpreted the same way as 'less than one day WFH', it should not be. Now, the last category includes every possibility that is more than one day, which could potentially be five or even more days. Testing this with evenly spaced categories, if available in other datasets, would be interesting because it allows the researcher to look at the marginal benefit of adding more WFH days. The variable *Working Less for Home* could be improved by using questions that come closer to the core of the variable: individuals that work less to be able to take care of the household. Changing the concept of productivity to a more measurable unit might project the results better. However, with this particular dataset, that was not possible.

Further, having data on hours worked, and WFH that is not self-reported but recorded by the company someone works for, might be more objective and truthful, and draw a better picture of the effects. Besides this, it would be interesting to have data on whether someone works from home during their employment hours, or during overtime. And it would be interesting as well to know if people work more within their employment hours or overtime as well. Having data on this would be informative on productivity as well, as working extra during overtime might be illustrative of lower productivity that has to be caught up on.

Aside from this, for future research, the model could be improved by including unemployed individuals that are employed for some of the time periods. This could pull in a group of respondents that previously could not combine work and home life, but through WFH see an opportunity to do so. But also the other way around, where individuals stopped working during COVID to take care of the family and housework. However, with the unbalanced panel, this is hard to introduce for this data.

Adding more specific data on childcare might be a good way to improve the validity of the study. However, a tradeoff must be made between very specific subgroups, where age and childcare options are combined, or focussing just on the care options and disregarding the age category, which leaves out the underlying characteristics of the age subgroup. The first might give specific answers, but requires a large sample to be able to produce significant results, while the latter loses validity in another way.

As sectors were widely spread and a large part of respondents did not fit into one of the categories, it might be interesting for future research to simplify the sector variable into blue-collar and white-collar workers or other forms of more generalized sectors, which creates bigger groups in the dataset. This would create more generalized answers, but it also might make the results more significant by increasing group size.

In this research, I could not account for organizational differences and specific rules provided for different sectors. However, it would be interesting to focus on the effects within a specific sector where WFH rules were implemented and to examine specific organizations to assess the impact of WFH measures within those organizations. Especially, including data on resources might shed a light on the JD-R theory, and its effects in the real world. This approach would allow for a more precise analysis by accounting for these differences.

Finally, this study looks into whether there is an effect of WFH on productivity, but it would also be interesting to see how much WFH would be beneficial, as this would give resources to employers for dealing with the new WFH-era.

Repeating this study over time makes it possible to find longer term effects of WFH. As this study shows the effects of teleworking around the COVID-19 pandemic, it might not yet be able to show changes in working hours. Changing the amount of hours worked might not be something as flexible as assumed. However, it is still interesting to see whether the effects will occur in the long term, as this flexible form of WFH has been the norm for longer.

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# A Summary Statistics

## A.1 Comprehensive Summary Statistics

**Table 10.** Comprehensive Summary Statistics

| Variable | Mean | Std. Dev. | Min. | Max. | Observations |
|---|---|---|---|---|---|
| **Gender** | 0.485 | 0.500 | 0 | 2 | N=8612 |
| Between | | 0.500 | 0 | 2 | n=3217 |
| Within | | 0.000 | 0.485 | 0.485 | T-bar = 2.67703 |
| **Age** | 45.409 | 11.865 | 16 | 75 | N=8621 |
| Between | | 12.472 | 16 | 75 | n=3226 |
| Within | | 1.173 | 42.209 | 47.909 | T-bar = 2.67235 |
| **Partner** | 0.799 | 0.401 | 0 | 1 | N=8621 |
| Between | | 0.394 | 0 | 1 | n=3226 |
| Within | | 0.115 | -0.035 | 1.632 | T-bar = 2.67235 |
| **Partner (living together)** | 0.730 | 0.444 | 0 | 1 | N=8621 |
| Between | | 0.437 | 0 | 1 | n=3226 |
| Within | | 0.125 | -0.103 | 1.564 | T-bar = 2.67235 |
| **Amount of children** | 1.367 | 1.238 | 0 | 9 | N=8621 |
| Between | | 1.237 | 0 | 9 | n=3226 |
| Within | | 0.174 | -0.633 | 4.033 | T-bar = 2.67235 |
| **Hours employed** | 33.581 | 7.897 | 1 | 80 | N=8621 |
| Between | | 8.122 | 1 | 80 | n=3226 |
| Within | | 1.890 | 10.915 | 59.831 | T-bar = 2.67235 |
| **Satisfaction with working hours** | 7.495 | 1.630 | 0 | 10 | N=8621 |
| Between | | 1.500 | 0 | 10 | n=3226 |
| Within | | 0.864 | 1.895 | 12.745 | T-bar = 2.67235 |
| **Commute minutes** | 28.695 | 21.409 | 0 | 210 | N=8621 |
| Between | | 20.638 | 0 | 180 | n=3226 |
| Within | | 7.720 | -61.305 | 174.695 | T-bar = 2.67235 |
| **Number of children cared for** | 0.165 | 0.606 | 0 | 12 | N=8621 |
| Between | | 0.544 | 0 | 6 | n=3226 |
| Within | | 0.333 | -5.835 | 6.165 | T-bar = 2.67235 |
| **Household division index** | 10.016 | 6.026 | 0 | 18 | N=8621 |
| Between | | 5.963 | 0 | 18 | n=3226 |
| Within | | 2.100 | -4.984 | 22.216 | T-bar = 2.67235 |
| **Care division index** | 1.148 | 2.707 | 0 | 24 | N=8621 |
| Between | | 2.530 | 0 | 24 | n=3226 |
| Within | | 1.359 | -10.852 | 20.348 | T-bar = 2.67235 |
| **Part days childcare** | 0.335 | 1.249 | 0 | 14 | N=8621 |
| Between | | 1.192 | 0 | 14 | n=3226 |
| Within | | 0.667 | -5.415 | 8.585 | T-bar = 2.67235 |

*Note.* Summary statistics for the complete sample, including mean, standard deviation, minimum, and maximum values for each variable. The sample includes various demographic and employment-related variables such as gender, age, partnership status, number of children, employment status, hours employed, satisfaction with working hours, commute minutes, and indices for household and care division tasks. The number of observations varies across variables.

**Table 11.** Comprehensive Summary Statistics (Full-time = 1)

| Variable | Mean | Std. Dev. | Min. | Max. | Observations |
|---|---|---|---|---|---|
| **Gender** | 0.279 | 0.449 | 0 | 1 | N=5301 |
| Between | | 0.463 | 0 | 1 | n=1869 |
| Within | | 0.000 | 0.279 | 0.279 | T-bar = 2.8363 |
| **Age** | 44.731 | 11.959 | 18 | 75 | N=5307 |
| Between | | 12.446 | 18 | 75 | n=1875 |
| Within | | 1.191 | 41.531 | 47.231 | T-bar = 2.8304 |
| **Partner** | 0.796 | 0.403 | 0 | 1 | N=5307 |
| Between | | 0.397 | 0 | 1 | n=1875 |
| Within | | 0.119 | -0.037 | 1.629 | T-bar = 2.8304 |
| **Partner (living together)** | 0.725 | 0.447 | 0 | 1 | N=5307 |
| Between | | 0.438 | 0 | 1 | n=1875 |
| Within | | 0.135 | -0.108 | 1.558 | T-bar = 2.8304 |
| **Amount of children** | 1.219 | 1.218 | 0 | 7 | N=5307 |
| Between | | 1.211 | 0 | 7 | n=1875 |
| Within | | 0.182 | -0.781 | 3.386 | T-bar = 2.8304 |
| **Hours employed** | 38.303 | 3.087 | 16 | 80 | N=5307 |
| Between | | 2.660 | 21.6 | 80 | n=1875 |
| Within | | 1.438 | 19.103 | 53.503 | T-bar = 2.8304 |
| **Satisfaction with working hours** | 7.433 | 1.607 | 0 | 10 | N=5307 |
| Between | | 1.469 | 0 | 10 | n=1875 |
| Within | | 0.857 | 2.433 | 12.433 | T-bar = 2.8304 |
| **Commute minutes** | 31.472 | 22.030 | 0 | 210 | N=5307 |
| Between | | 21.246 | 0 | 180 | n=1875 |
| Within | | 8.391 | -58.528 | 177.472 | T-bar = 2.8304 |
| **Number of children cared for** | 0.034 | 0.243 | 0 | 3 | N=5307 |
| Between | | 0.204 | 0 | 3 | n=1875 |
| Within | | 0.157 | -1.466 | 2.534 | T-bar = 2.8304 |
| **Household division index** | 9.296 | 6.180 | 0 | 18 | N=5307 |
| Between | | 6.110 | 0 | 18 | n=1875 |
| Within | | 2.147 | -5.704 | 21.496 | T-bar = 2.8304 |
| **Care division index** | 0.868 | 2.328 | 0 | 24 | N=5307 |
| Between | | 2.122 | 0 | 24 | n=1875 |
| Within | | 1.341 | -11.132 | 20.068 | T-bar = 2.8304 |
| **Part days childcare** | 0.324 | 1.232 | 0 | 12 | N=5307 |
| Between | | 1.110 | 0 | 8 | n=1875 |
| Within | | 0.698 | -4.676 | 8.324 | T-bar = 2.8304 |

*Note.* Summary statistics for full-time employees, including mean, standard deviation, minimum, and maximum values for each variable. The sample includes various demographic and employment-related variables such as gender, age, partnership status, number of children, employment status, hours employed, satisfaction with working hours, commute minutes, and indices for household and care division tasks. The number of observations varies across variables.

**Table 12.** Comprehensive Summary Statistics (Full-time = 0)

| Variable | Mean | Std. Dev. | Min. | Max. | Observations |
|---|---|---|---|---|---|
| **Gender** | 0.814 | 0.390 | 0 | 2 | N=3311 |
| Between | | 0.396 | 0 | 2 | n=1348 |
| Within | | 0.000 | 0.814 | 0.814 | T-bar = 2.4562 |
| **Age** | 46.494 | 11.633 | 16 | 74 | N=3314 |
| Between | | 12.352 | 16 | 73 | n=1351 |
| Within | | 1.143 | 43.744 | 48.894 | T-bar = 2.453 |
| **Partner** | 0.803 | 0.398 | 0 | 1 | N=3314 |
| Between | | 0.391 | 0 | 1 | n=1351 |
| Within | | 0.109 | -0.031 | 1.603 | T-bar = 2.453 |
| **Partner (living together)** | 0.739 | 0.439 | 0 | 1 | N=3314 |
| Between | | 0.436 | 0 | 1 | n=1351 |
| Within | | 0.108 | -0.094 | 1.539 | T-bar = 2.453 |
| **Amount of children** | 1.603 | 1.233 | 0 | 9 | N=3314 |
| Between | | 1.234 | 0 | 9 | n=1351 |
| Within | | 0.160 | -0.064 | 4.270 | T-bar = 2.453 |
| **Hours employed** | 26.020 | 7.355 | 1 | 48 | N=3314 |
| Between | | 7.252 | 1 | 40 | n=1351 |
| Within | | 2.446 | 3.354 | 52.270 | T-bar = 2.453 |
| **Satisfaction with working hours** | 7.596 | 1.660 | 0 | 10 | N=3314 |
| Between | | 1.541 | 0 | 10 | n=1351 |
| Within | | 0.876 | 1.996 | 12.846 | T-bar = 2.453 |
| **Commute minutes** | 24.248 | 19.574 | 0 | 180 | N=3314 |
| Between | | 18.882 | 0 | 180 | n=1351 |
| Within | | 6.506 | -55.752 | 71.748 | T-bar = 2.453 |
| **Number of children cared for** | 0.376 | 0.889 | 0 | 12 | N=3314 |
| Between | | 0.765 | 0 | 6 | n=1351 |
| Within | | 0.499 | -5.624 | 6.376 | T-bar = 2.453 |
| **Household division index** | 11.170 | 5.582 | 0 | 18 | N=3314 |
| Between | | 5.614 | 0 | 18 | n=1351 |
| Within | | 2.022 | -3.230 | 23.170 | T-bar = 2.453 |
| **Care division index** | 1.596 | 3.172 | 0 | 24 | N=3314 |
| Between | | 2.955 | 0 | 15 | n=1351 |
| Within | | 1.386 | -10.404 | 17.596 | T-bar = 2.453 |
| **Part days childcare** | 0.352 | 1.275 | 0 | 14 | N=3314 |
| Between | | 1.298 | 0 | 14 | n=1351 |
| Within | | 0.614 | -5.398 | 8.602 | T-bar = 2.453 |

*Note.* Summary statistics for part-time employees, including mean, standard deviation, minimum, and maximum values for each variable. The sample includes various demographic and employment-related variables such as gender, age, partnership status, number of children, employment status, hours employed, satisfaction with working hours, commute minutes, and indices for household and care division tasks. The number of observations varies across variables.

## A.2 Full-time and Part-time Transition

**Table 13.** Full-Time and Part-Time Transition

| | **Part-time** | **Full-time** | **Total** |
|---|---|---|---|
| **Part-time** | 95.73 | 4.27 | 100.00 |
| **Full-time** | 3.58 | 96.42 | 100.00 |
| **Total** | 37.55 | 62.45 | 100.00 |

*Note.* The table shows the distribution and transition of full-time and part-time statuses. Rows represent the full-time status at time 't' and columns the full-time status at time 't+1'. The values are expressed as percentages. Cells show the percentage of individuals who transitioned between statusses over time.

## A.3 Children at Home

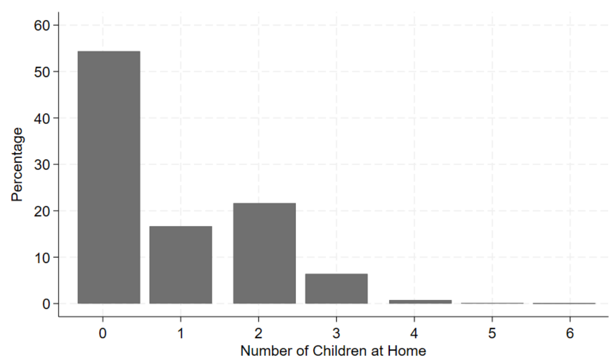


*Figure 6: Amount of Children Living at Home.* This figure shows the distribution of how many children an individual has living at home. The x-axis represents the number of children living at home, and the y-axis represents the percentage of individuals with that number of children.

## A.4 Employment and Work Between Genders

### A.4.1 Gender Distribution Over Full-time Status

**Table 14.** Gender Distribution Between Full-time and Part-time Employees

| **Employment Status** | **Male** | **Female** | **Other** | **Missing** | **Total** |
|---|---|---|---|---|---|
| Part-time (0) | 618 | 2,692 | 1 | 3 | 3,314 |
| Full-time (1) | 3,821 | 1,480 | 0 | 6 | 5,307 |
| **Total** | 4,439 | 4,172 | 1 | 9 | 8,621 |

*Note.* The table shows the distribution of employees by gender (male, female, and other) and employment status (part-time or full-time), including a category for missing data.

### A.4.2 Evolution of Employment and Work Hours between Genders

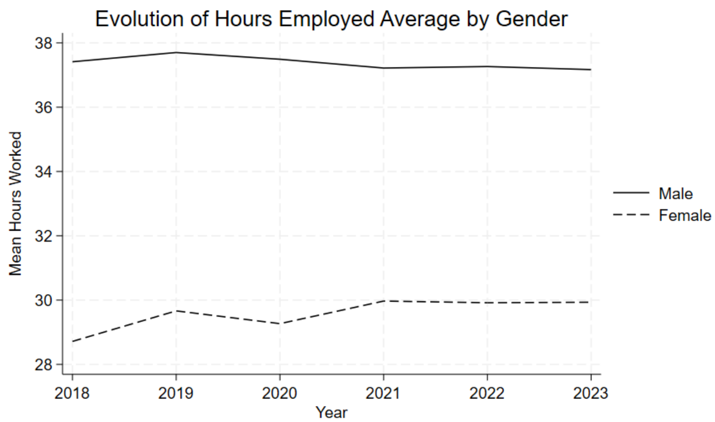


*Figure 7: Hours Employed per Year and full-time Status.* This figure displays the mean of hours employed by men and women over the years 2018-2023.

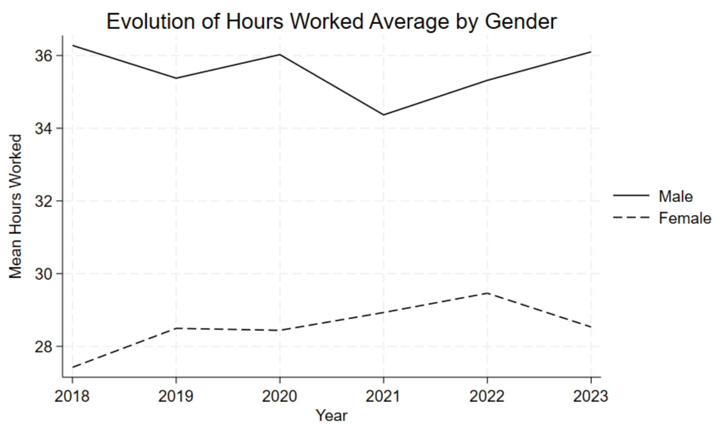


*Figure 8: Hours Worked per Year and full-time Status.* This figure displays the mean of hours worked on average by men and women over the years 2018-2023.

## A.5 Changes in Working Less

**Table 15.** Individuals Working Less for Home Tasks or Childcare

| Year | Less Hours (Home) | More Hours (Home) | Less Hours (Children) | More Hours (Children) |
|---|---|---|---|---|
| **2018** | 0 | 0 | 0 | 0 |
| **2019** | 0 | 2 | 21 | 26 |
| **2020** | 0 | 0 | 14 | 30 |
| **2021** | 0 | 0 | 42 | 37 |
| **2022** | 0 | 0 | 28 | 32 |
| **2023** | 0 | 0 | 30 | 30 |
| **Total** | 0 | 2 | 135 | 155 |

*Note.* Data for individuals switching categories for working less or more hours for home tasks and childcare across different years. An individual is counted if they switched to working less hours for Home or Children, or to working more hours for this reason. The categories include "Less Hours (Home)," "More Hours (Home)," "Less Hours (Children)," and "More Hours (Children)" for each year from 2018 to 2023.

## A.6 Satisfaction with Working Hours

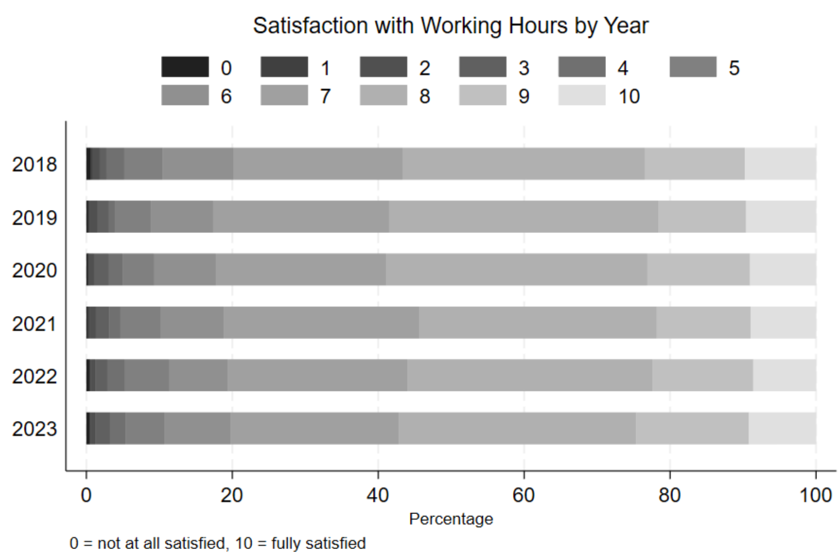


*Figure 9: Satisfaction with Working Hours.* This figure illustrates the distribution of satisfaction with working hours from 2018 to 2023. The scale ranges from 0 (not at all satisfied) to 10 (fully satisfied). Each bar represents a specific year, showing the percentage of respondents who rated their satisfaction at each level of the scale. The figure highlights trends in employee satisfaction with their working hours over time

## A.7 Sector of Employment Distribution

| Sector | 2018 | 2019 | 2020 | 2021 | 2022 | 2023 | Total |
|---|---|---|---|---|---|---|---|
| Agriculture, forestry, fishery, hunting | 21 | 14 | 20 | 19 | 16 | 20 | 110 |
| Mining | 0 | 0 | 0 | 0 | 1 | 0 | 1 |
| Industrial production | 182 | 151 | 155 | 146 | 154 | 118 | 906 |
| Utilities production, distribution, and/or trade | 14 | 14 | 17 | 14 | 19 | 16 | 94 |
| Construction | 62 | 64 | 61 | 58 | 68 | 63 | 376 |
| Retail trade | 123 | 78 | 111 | 99 | 112 | 104 | 627 |
| Catering | 33 | 29 | 38 | 28 | 27 | 18 | 173 |
| Transport, storage, and communication | 96 | 79 | 100 | 89 | 92 | 86 | 542 |
| Financial | 83 | 70 | 79 | 82 | 90 | 73 | 477 |
| Business services | 112 | 87 | 96 | 100 | 93 | 89 | 577 |
| Government services | 162 | 125 | 145 | 145 | 150 | 127 | 854 |
| Education | 125 | 100 | 126 | 124 | 140 | 134 | 749 |
| Healthcare and welfare | 317 | 217 | 278 | 268 | 282 | 246 | 1608 |
| Environmental services, culture, recreation, and other services | 38 | 25 | 38 | 27 | 24 | 19 | 171 |
| Other | 250 | 158 | 241 | 240 | 242 | 225 | 1356 |

*Note.* Summary statistics for the sector of employment by year, showing the distribution of respondents across the employment sectors from 2018 to 2023. The table includes counts for each sector and year, with a total count for each sector over the entire period.

# B Fixed Effect Assumptions

## B.1 Hausman Test Results

**Table 16.** Hausman Test for Fixed Effects vs. Random Effects

| | Coefficients | | Difference | |
|---|---|---|---|---|
| Variable | *FE (b)* | *RE (B)* | *(b-B)* | *Std. Error* |
| Days WFH (1) | 2.366384 | 4.045129 | -1.678745 | 0.7560289 |
| Days WFH (2) | 0.8728202 | 2.334882 | -1.462061 | 0.7618054 |
| Days WFH (3) | 1.398848 | 2.205308 | -0.806460 | 1.088093 |
| COVID 1 | 0.2459394 | -0.0669727 | 0.3129121 | 0.753966 |
| COVID 2 | -0.2761187 | -0.6630659 | 0.3869472 | 1.225709 |
| COVID 3 | 0.3717464 | -0.2389646 | 0.6107109 | 1.688009 |
| Days WFH (1) * COVID 1 | -2.733282 | -2.544711 | -0.1885708 | 0.6101453 |
| Days WFH (1) * COVID 2 | -1.138368 | -1.235837 | 0.0974692 | 0.7355704 |
| Days WFH (1) * COVID 3 | -2.845416 | -1.840809 | -1.004607 | 0.912967 |
| Days WFH (2) * COVID 1 | 1.309866 | 1.20013 | 0.1097358 | 0.6080744 |
| Days WFH (2) * COVID 2 | 1.431217 | 1.746371 | -0.3151534 | 0.6876216 |
| Days WFH (2) * COVID 3 | 0.5803905 | 0.9062829 | -0.3258924 | 0.8406444 |
| Days WFH (3) * COVID 1 | -0.1916346 | 0.0131995 | -0.2048342 | 0.8500883 |
| Days WFH (3) * COVID 2 | 0.3123609 | 0.6984188 | -0.3860579 | 0.9886318 |
| Days WFH (3) * COVID 3 | -0.528749 | 0.1349613 | -0.6637103 | 1.031262 |
| Age | -0.4596025 | -0.0823766 | -0.3772258 | 0.4668432 |
| Partner (Living Together) | -4.142688 | -6.457024 | 2.314336 | 1.128505 |
| Children (0-4) | -0.9987086 | -0.931524 | -0.0671846 | 0.7141706 |
| Children (5-11) | 0.2853578 | -0.8492027 | 1.134561 | 0.7964847 |
| Children (12+) | 1.667242 | -0.4232059 | 2.090448 | 0.8853555 |
| Part Days Childcare | -0.231547 | -0.0263869 | -0.2051601 | 0.1233608 |
| Commute Minutes | 0.008371 | 0.0413699 | -0.0329989 | 0.0128939 |
| Industrial Production | 0.6256585 | 9.333736 | -8.708078 | 9.584481 |
| Utilities Production, Distribution, and/or Trade | 1.749359 | 0.82521 | 0.9241487 | 2.920838 |
| Construction | 6.354468 | -0.3110712 | 6.665539 | 3.795462 |
| Retail Trade | 0.861453 | 0.0962513 | 0.7652017 | 3.486304 |
| Catering | -0.0666558 | -2.369127 | 2.302472 | 3.045188 |
| Transport, Storage, and Communication | 1.618211 | -1.815169 | 3.433379 | 3.750991 |
| Financial | 2.552662 | 0.7334627 | 1.819199 | 3.021703 |
| Business Services | -1.575378 | -2.53262 | 0.9572424 | 3.154009 |
| Government Services | 0.380247 | 0.7571476 | -0.3769005 | 2.953023 |
| Education | 0.661869 | -1.576705 | 2.238574 | 3.015903 |
| Healthcare and Welfare | 0.7895103 | -0.4053863 | 1.194897 | 3.128571 |
| Environmental Services, Culture, Recreation, and Other Services | 1.128296 | -5.625611 | 6.753907 | 2.893292 |
| Other | -1.540008 | -2.716196 | 1.176189 | 3.294419 |
| Unemployed | 0.8365928 | -1.766784 | 2.603377 | 2.662066 |
| Satisfaction Working Hours | -0.3080406 | -0.2390953 | -0.0689452 | 0.0973994 |
| Household Division Index | -0.3394355 | -0.5833984 | 0.2439629 | 0.0630307 |
| Care Division Index | -0.0130254 | -0.2304648 | 0.2174394 | 0.0604782 |
| *Test of H0: Difference in coefficients not systematic* | | | | |
| chi2(39) | | | 95.87 | |
| Prob > chi2 | | | 0.0000 | |

*Note.* This table presents the results of the Hausman test comparing fixed effects (FE) and random effects (RE) models. The coefficients for each variable under both models are shown, along with the difference between these coefficients and the standard error of the difference. The Hausman test statistic (chi2) is provided at the bottom, indicating whether the difference in coefficients is statistically significant. A significant test result suggests that the fixed effects model is more appropriate than the random effects model for this data.

## B.2 Variance Inflation Factor Test

**Table 17.** Variance Inflation Factor (VIF) Results

| Variable | VIF | 1/VIF |
|---|---|---|
| Days WFH (1) | 2.28 | 0.439402 |
| Days WFH (2) | 3.01 | 0.332755 |
| Days WFH (3) | 11.58 | 0.086361 |
| COVID 1 | 1.69 | 0.593034 |
| COVID 2 | 1.88 | 0.531913 |
| COVID 3 | 2.02 | 0.494436 |
| Days WFH (1) * COVID 1 | 1.57 | 0.638216 |
| Days WFH (1) * COVID 2 | 1.33 | 0.750877 |
| Days WFH (1) * COVID 3 | 1.59 | 0.629855 |
| Days WFH (2) * COVID 1 | 1.68 | 0.594470 |
| Days WFH (2) * COVID 2 | 1.55 | 0.643493 |
| Days WFH (2) * COVID 3 | 2.12 | 0.472617 |
| Days WFH (3) * COVID 1 | 2.08 | 0.480100 |
| Days WFH (3) * COVID 2 | 4.81 | 0.207978 |
| Days WFH (3) * COVID 3 | 8.42 | 0.118722 |
| Age | 1.69 | 0.592634 |
| Partner (Living Together) | 3.18 | 0.314004 |
| Children (0-4) | 2.56 | 0.390937 |
| Children (5-11) | 1.36 | 0.737557 |
| Children (12+) | 1.68 | 0.594189 |
| Part Days Childcare | 2.20 | 0.454795 |
| Commute Minutes | 1.10 | 0.908430 |
| Industrial Production | 1.01 | 0.987874 |
| Utilities Production, Distribution, and/or Trade | 8.30 | 0.120438 |
| Construction | 1.85 | 0.541783 |
| Retail Trade | 4.24 | 0.235679 |
| Catering | 6.25 | 0.160006 |
| Transport, Storage, and Communication | 2.53 | 0.394858 |
| Financial | 5.58 | 0.179197 |
| Business Services | 5.09 | 0.196288 |
| Government Services | 5.89 | 0.169700 |
| Education | 7.98 | 0.125322 |
| Healthcare and Welfare | 7.16 | 0.139686 |
| Environmental Services, Culture, Recreation, and Other Services | 12.79 | 0.078165 |
| Other | 2.52 | 0.396481 |
| Satisfaction Working Hours | 1.05 | 0.953322 |
| Household Division Index | 3.06 | 0.326612 |
| Care Division Index | 1.82 | 0.550599 |
| Mean VIF | 3.84 | |

*Note.* This table presents the Variance Inflation Factor (VIF) results for the variables used in the regression analysis. VIF measures the degree of multicollinearity among the variables. A VIF value above 10 indicates high multicollinearity. The 1/VIF column provides the tolerance values, which are the reciprocal of VIF. The mean VIF for the model is 3.84.

## B.3 Serial Correlation Test

**Table 18.** Regression Results

| **Source** | **SS** | **df** | **MS** | **F-statistic** |
|---|---|---|---|---|
| Model | 43373.9851 | 1 | 43373.9851 | 553.96 |
| Residual | 365574.978 | 4669 | 78.298346 | |
| Total | 408948.963 | 4670 | 87.569371 | |
| **Variable** | **Coefficient** | **SE** | **t** | **P-value** |
| Lagged Residuals | -0.3260131 | 0.0138515 | -23.54 | 0.000 |
| Constant | -0.0729069 | 0.1294845 | -0.56 | 0.573 |

*Note.* This table presents the results of the serial correlation test. The top panel displays the sum of squares (SS), degrees of freedom (df), mean square (MS), and F-statistic for the model and residuals. The bottom panel shows the regression coefficients, standard errors (SE), t-values, and p-values for the lagged residuals and the constant term. A significant coefficient for the lagged residuals indicates the presence of serial correlation.

# C Full Results Primary Analysis

## C.1 Hypothesis 1

**Table 19.** *FE Regression Results: Impact of WFH Days on Hours Worked Across COVID Periods*

| | Worked Less Because of Responsibilities | | | |
|---|---|---|---|---|
| | **Full-time** | **Full-time** | **Part-time** | **Part-time** |
| **Days WFH** | | | | |
| <1 day | 2.799* | 3.255* | 0.117 | -0.091 |
| | (1.351) | (1.341) | (1.526) | (1.550) |
| 1 day | 1.547 | 2.000 | -2.268 | -2.404 |
| | (1.792) | (1.735) | (1.651) | (1.656) |
| >1 day | 1.533 | 1.258 | -0.641 | -0.816 |
| | (1.901) | (1.939) | (3.145) | (3.233) |
| **COVID Period** | | | | |
| COVID 1 | -0.630 | 0.271 | 0.447 | 0.749 |
| | (0.687) | (1.258) | (0.483) | (1.254) |
| COVID 2 | -2.670** | -0.912 | 0.618 | 1.425 |
| | (0.727) | (1.780) | (0.598) | (2.014) |
| Post-COVID | -2.217** | -0.021 | 0.819 | 1.753 |
| | (0.640) | (2.379) | (0.594) | (2.656) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | -2.066 | -2.297 | -3.869 | -3.593 |
| | (1.857) | (1.840) | (2.384) | (2.432) |
| <1 day * COVID 2 | -1.572 | -2.192 | 2.382 | 2.131 |
| | (2.590) | (2.613) | (2.092) | (2.142) |
| <1 day * Post-COVID | -1.709 | -2.373 | -2.677 | -2.690 |
| | (2.309) | (2.317) | (2.304) | (2.355) |
| 1 day * COVID 1 | 1.712 | 1.477 | 1.376 | 1.046 |
| | (2.212) | (2.213) | (2.065) | (1.892) |
| 1 day * COVID 2 | 3.072 | 2.906 | -0.191 | -0.005 |
| | (2.645) | (2.596) | (1.937) | (1.921) |
| 1 day * Post-COVID | 1.479 | 0.937 | 1.274 | 1.404 |
| | (2.148) | (2.088) | (1.820) | (1.850) |
| >1 day * COVID 1 | -0.790 | -0.519 | 2.682 | 2.931 |
| | (2.428) | (2.451) | (3.182) | (3.234) |
| >1 day * COVID 2 | 0.968 | 1.353 | 1.057 | 1.191 |
| | (2.004) | (2.019) | (3.172) | (3.239) |
| >1 day * Post-COVID | 0.109 | 0.764 | -0.123 | 0.266 |

| | Full-time | Full-time | Part-time | Part-time |
|---|---|---|---|---|
| | (1.898) | (1.921) | (3.120) | (3.242) |
| **Age respondent** | | -0.703 | | -0.327 |
| | | (0.657) | | (0.695) |
| **Live Together** | | -5.306** | | -0.700 |
| | | (1.595) | | (1.355) |
| **Children (0-4)** | | -1.916 | | 0.899 |
| | | (1.435) | | (1.006) |
| **Children (5-11)** | | 0.775 | | 0.134 |
| | | (1.429) | | (0.841) |
| **Children (12+)** | | 2.519 | | 0.476 |
| | | (1.391) | | (0.772) |
| **Partdays Child Care** | | -0.187 | | -0.344 |
| | | (0.255) | | (0.232) |
| **Commute Minutes** | | 0.017 | | -0.012 |
| | | (0.022) | | (0.028) |
| **Employment Sector** | | | | |
| Mining | | 1.908 | | |
| | | (4.519) | | |
| Industrial production | | 2.414 | | 4.616 |
| | | (3.509) | | (7.160) |
| Utilities production, distribution, and/or trade | | 9.858 | | 0.101 |
| | | (5.299) | | (6.941) |
| Construction | | -0.354 | | 16.636 |
| | | (5.266) | | (13.530) |
| Retail trade | | 0.178 | | 0.202 |
| | | (4.126) | | (6.525) |
| Catering | | 6.985 | | -1.747 |
| | | (5.697) | | (6.036) |
| Transport, storage, and communication | | 5.160 | | -3.151 |
| | | (3.899) | | (7.296) |
| Financial | | -0.679 | | 1.367 |
| | | (3.810) | | (7.397) |
| Business services | | 3.331 | | -3.853 |
| | | (3.809) | | (6.859) |
| Government services | | 1.925 | | 1.170 |
| | | (3.755) | | (6.810) |

| | Full-time | Full-time | Part-time | Part-time |
|---|---|---|---|---|
| Education | | 2.597 | | -0.151 |
| | | (4.069) | | (7.234) |
| Healthcare and welfare | | 2.105 | | 0.720 |
| | | (3.752) | | (6.578) |
| Environmental services, culture, recreation, and other services | | 1.494 | | -3.625 |
| | | (3.837) | | (7.042) |
| Other | | 2.492 | | -0.019 |
| | | (3.385) | | (6.466) |
| **Satisfaction Working Hours** | | -0.391** | | -0.263** |
| | | (0.101) | | (0.080) |
| **Household Division Index** | | 0.158 | | -0.252* |
| | | (0.116) | | (0.101) |
| **Care Division Index** | | -0.391* | | -0.263** |
| | | (0.101) | | (0.080) |
| **Intercept** | 37.131** | 72.912** | 24.814** | 43.963 |
| | (0.419) | (28.024) | (0.330) | (30.338) |
| **Number of observations** | 5307 | 5307 | 3314 | 3314 |

*Note.* This table provides the outcomes for regression of WFH Days on Hours Worked. WFH stands for 'Work From Home'. Columns 1 and 2 present the outcomes for employees labeled full-time, columns 3 and 4 present the outcomes for employees labeled part-time. Standard errors are in parentheses. * $p < .01$, ** $p < .05$

### C.2 Hypothesis 2

**Table 20.** *FE Regression Results: Impact of WFH Days on Working Part-time for Home Responsibilities*

| Working Less Because of Responsibilities at Home | | | | |
|---|---|---|---|---|
| | Full sample | Full sample | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | -0.003 | -0.003 | -0.007 | -0.009 |
| | (0.002) | (0.002) | (0.004) | (0.004) |
| 1 day | -0.002* | -0.002 | -0.006* | -0.006 |
| | (0.001) | (0.001) | (0.003) | (0.004) |
| >1 day | -0.002* | -0.001 | -0.005* | -0.001 |
| | (0.001) | (0.001) | (0.002) | (0.005) |
| **COVID Period** | | | | |
| COVID 1 | -0.002* | 0.003 | -0.006* | 0.009 |
| | (0.001) | (0.002) | (0.003) | (0.005) |
| COVID 2 | -0.004* | 0.005 | -0.010* | 0.015 |
| | (0.002) | (0.003) | (0.004) | (0.009) |
| Post-COVID | -0.004* | 0.008 | -0.011* | 0.022 |
| | (0.002) | (0.004) | (0.005) | (0.012) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | 0.000 | 0.001 | -0.004 | -0.003 |
| | (0.002) | (0.002) | (0.009) | (0.007) |
| <1 day * COVID 2 | 0.004* | 0.004* | 0.009* | 0.005 |
| | (0.002) | (0.002) | (0.004) | (0.005) |
| <1 day * Post-COVID | 0.004* | 0.004* | 0.010* | 0.009* |
| | (0.002) | (0.002) | (0.005) | (0.004) |
| 1 day * COVID 1 | 0.003* | 0.003* | 0.007* | 0.004 |
| | (0.001) | (0.001) | (0.003) | (0.003) |
| 1 day * COVID 2 | 0.004* | 0.003 | 0.010* | 0.009 |
| | (0.002) | (0.002) | (0.005) | (0.005) |
| 1 day * Post-COVID | 0.004* | 0.004 | 0.011* | 0.011 |
| | (0.002) | (0.002) | (0.005) | (0.006) |
| >1 day * COVID 1 | 0.003* | 0.002 | 0.006* | 0.006 |
| | (0.001) | (0.001) | (0.003) | (0.005) |
| >1 day * COVID 2 | 0.004* | 0.003* | 0.009* | 0.005 |
| | (0.002) | (0.001) | (0.004) | (0.005) |
| >1 day * Post-COVID | 0.004* | 0.003 | 0.010* | 0.005 |
| | (0.002) | (0.002) | (0.005) | (0.006) |

| Days WFH and COVID Period Interaction (cont.) | | | | |
|---|---|---|---|---|
| | Full sample | Full sample | Part-time | Part-time |
| **Age respondent** | | -0.003* | | -0.009* |
| | | (0.001) | | (0.004) |
| **Live Together** | | 0.014 | | 0.035 |
| | | (0.010) | | (0.028) |
| **Children (0-4)** | | 0.001 | | 0.003 |
| | | (0.001) | | (0.003) |
| **Children (5-11)** | | 0.002 | | 0.006 |
| | | (0.001) | | (0.003) |
| **Children (12+)** | | 0.000 | | 0.002 |
| | | (0.001) | | (0.004) |
| **Part Days Childcare** | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) |
| **Commute Minutes** | | 0.000 | | 0.000 |
| | | (0.000) | | (0.000) |
| **Employment Sector** | | | | |
| Mining | | -0.000 | | |
| | | (0.006) | | |
| Industrial production | | 0.001 | | 0.000 |
| | | (0.002) | | (0.006) |
| Utilities production, distribution, and/or trade | | -0.000 | | -0.012 |
| | | (0.002) | | (0.012) |
| Construction | | 0.003 | | 0.010 |
| | | (0.002) | | (0.009) |
| Retail trade | | 0.012 | | 0.025 |
| | | (0.012) | | (0.027) |
| Catering | | 0.001 | | -0.006 |
| | | (0.002) | | (0.006) |
| Transport, storage, and communication | | 0.001 | | -0.004 |
| | | (0.001) | | (0.007) |
| Financial | | 0.000 | | -0.013 |
| | | (0.002) | | (0.018) |
| Business services | | 0.002 | | 0.006 |
| | | (0.002) | | (0.007) |
| Government services | | 0.002 | | -0.004 |
| | | (0.002) | | (0.006) |

| Days WFH and COVID Period Interaction (cont.) | | | | |
|---|---|---|---|---|
| | Full sample | Full sample | Part-time | Part-time |
| Education | | -0.000 | | -0.003 |
| | | (0.002) | | (0.006) |
| Healthcare and welfare | | 0.007 | | 0.003 |
| | | (0.006) | | (0.008) |
| Environmental services, culture, recreation, and other services | | -0.021 | | -0.057 |
| | | (0.022) | | (0.051) |
| Other | | -0.001 | | -0.008 |
| | | (0.002) | | (0.008) |
| **Satisfaction Working Hours** | | 0.001 | | 0.001 |
| | | (0.001) | | (0.001) |
| **Household Division Index** | | 0.001 | | 0.001 |
| | | (0.000) | | (0.001) |
| **Care Division Index** | | -0.000 | | -0.000 |
| | | (0.000) | | (0.000) |
| **Intercept** | 0.003** | 0.128* | 0.009** | 0.359* |
| | (0.001) | (0.056) | (0.003) | (0.160) |
| **Number of observations** | 8621 | 8621 | 3314 | 3314 |

*Note.* This table provides the outcomes for regression of WFH Days on Working Less for Home. WFH stands for 'Work From Home'. Columns 1 and 2 present the outcomes for employees labeled full-time, columns 3 and 4 present the outcomes for employees labeled part-time. Standard errors are in parentheses. * p < .01, ** p < .05

### C.3 Hypothesis 3a

**Table 21.** *FE Regression Results: Impact of WFH Days on Working Less for Childcare Responsibilities*

| **Working Less for Childcare Responsibilities** | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | -0.001 | -0.011 | 0.033 | 0.012 |
| | (0.014) | (0.014) | (0.063) | (0.063) |
| 1 day | 0.017 | 0.004 | 0.044 | 0.041 |
| | (0.014) | (0.014) | (0.057) | (0.056) |
| >1 day | -0.010 | -0.013 | -0.127 | -0.137 |
| | (0.022) | (0.016) | (0.071) | (0.076) |
| **COVID Period** | | | | |
| COVID 1 | 0.013* | -0.004 | -0.096** | -0.002 |
| | (0.007) | (0.011) | (0.018) | (0.035) |
| COVID 2 | 0.017* | -0.018 | -0.094** | 0.046 |
| | (0.008) | (0.016) | (0.021) | (0.053) |
| Post-COVID | 0.018 | -0.029 | -0.094** | 0.094 |
| | (0.009) | (0.021) | (0.021) | (0.071) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | 0.010 | 0.009 | 0.076 | 0.061 |
| | (0.016) | (0.014) | (0.092) | (0.091) |
| <1 day * COVID 2 | 0.046 | 0.052* | -0.111 | -0.104 |
| | (0.027) | (0.025) | (0.107) | (0.103) |
| <1 day * Post-COVID | 0.014 | 0.033 | -0.115 | -0.119 |
| | (0.017) | (0.017) | (0.115) | (0.118) |
| 1 day * COVID 1 | -0.014 | -0.010 | 0.012 | -0.004 |
| | (0.015) | (0.015) | (0.066) | (0.064) |
| 1 day * COVID 2 | -0.007 | -0.008 | -0.000 | -0.008 |
| | (0.020) | (0.020) | (0.063) | (0.061) |
| 1 day * Post-COVID | -0.018 | -0.003 | -0.084 | -0.092 |
| | (0.017) | (0.017) | (0.079) | (0.078) |
| >1 day * COVID 1 | 0.023 | 0.020 | 0.192** | 0.179* |
| | (0.027) | (0.025) | (0.070) | (0.071) |
| >1 day * COVID 2 | 0.008 | 0.011 | 0.098 | 0.113 |
| | (0.021) | (0.017) | (0.074) | (0.077) |
| >1 day * Post-COVID | 0.017 | 0.020 | 0.106 | 0.118 |
| | (0.020) | (0.016) | (0.072) | (0.078) |

| Days WFH and COVID Period Interaction (cont.) | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Age respondent** | | 0.010 | | -0.050** |
| | | (0.006) | | (0.019) |
| **Do you live together with this partner?** | | -0.005 | | 0.081 |
| | | (0.019) | | (0.052) |
| **Children (0-4)** | | 0.134** | | 0.007 |
| | | (0.030) | | (0.057) |
| **Children (5-11)** | | 0.097** | | 0.049 |
| | | (0.027) | | (0.052) |
| **Children (12+)** | | 0.077* | | -0.009 |
| | | (0.031) | | (0.041) |
| **Part Days Childcare** | | 0.011* | | 0.002 |
| | | (0.006) | | (0.014) |
| **Commute Minutes** | | -0.000* | | 0.001 |
| | | (0.000) | | (0.001) |
| **Employment Sector** | | | | |
| Mining | | 0.004 | | |
| | | (0.047) | | |
| Industrial production | | -0.000 | | 0.193 |
| | | (0.026) | | (0.149) |
| Utilities production, distribution, and/or trade | | -0.106 | | -0.196 |
| | | (0.063) | | (0.294) |
| Construction | | -0.026 | | 0.015 |
| | | (0.023) | | (0.100) |
| Retail trade | | -0.038 | | 0.080 |
| | | (0.040) | | (0.110) |
| Catering | | -0.053 | | 0.072 |
| | | (0.032) | | (0.115) |
| Transport, storage, and communication | | -0.022 | | -0.123 |
| | | (0.028) | | (0.111) |
| Financial | | -0.024 | | 0.131 |
| | | (0.039) | | (0.172) |
| Business services | | 0.012 | | 0.091 |
| | | (0.031) | | (0.134) |
| Government services | | -0.050 | | 0.069 |

| Days WFH and COVID Period Interaction (cont.) | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| | | (0.031) | | (0.104) |
| Education | | -0.016 | | 0.157 |
| | | (0.036) | | (0.100) |
| Healthcare and welfare | | -0.007 | | 0.164* |
| | | (0.033) | | (0.084) |
| Environmental services, culture, recreation, and other services | | 0.033 | | -0.119 |
| | | (0.037) | | (0.108) |
| Other | | -0.035 | | -0.093 |
| | | (0.024) | | (0.073) |
| **Satisfaction Working Hours** | | 0.000 | | -0.006 |
| | | (0.002) | | (0.006) |
| **Household Division Index** | | -0.000 | | 0.004 |
| | | (0.001) | | (0.003) |
| **Care Division Index** | | 0.004 | | 0.005 |
| | | (0.003) | | (0.005) |
| **Intercept** | 0.009* | -0.492 | 0.254** | 2.303** |
| | (0.005) | (0.262) | (0.012) | (0.852) |
| **Number of observations** | 5307 | 5307 | 3314 | 3314 |

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on Working Less for Children across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.

## C.4 Hypothesis 3b

**Table 22.** *FE Regression Results: Impact of WFH Days on Hours Worked for Childcare Responsibilities*

| **Days WFH and COVID Period Interaction** | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | 0.147 | 0.055 | 0.205 | 0.024 |
| | (0.102) | (0.102) | (0.917) | (0.928) |
| 1 day | 0.217 | 0.105 | -0.363 | -0.356 |
| | (0.118) | (0.114) | (0.516) | (0.513) |
| >1 day | -0.017 | -0.028 | -1.250** | -1.290** |
| | (0.171) | (0.122) | (0.447) | (0.488) |
| **COVID Period** | | | | |
| COVID 1 | 0.179* | -0.011 | -1.086** | -0.194 |
| | (0.072) | (0.103) | (0.219) | (0.439) |
| COVID 2 | 0.200** | -0.161 | -1.028** | 0.258 |
| | (0.068) | (0.133) | (0.255) | (0.678) |
| Post-COVID | 0.216** | -0.275 | -1.293** | 0.464 |
| | (0.081) | (0.173) | (0.265) | (0.905) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 1 | -0.046 | -0.066 | 0.336 | 0.192 |
| | (0.112) | (0.102) | (1.065) | (1.050) |
| <1 day * COVID 2 | 0.277 | 0.331 | -0.975 | -0.856 |
| | (0.223) | (0.244) | (1.020) | (1.008) |
| <1 day * Post-COVID | -0.004 | 0.173 | -0.104 | -0.221 |
| | (0.123) | (0.138) | (1.157) | (1.145) |
| 1 day * COVID 1 | -0.155 | -0.133 | 0.781 | 0.598 |
| | (0.123) | (0.125) | (0.526) | (0.531) |
| 1 day * COVID 2 | -0.054 | -0.069 | 1.606 | 1.460 |
| | (0.219) | (0.213) | (0.938) | (0.912) |
| 1 day * Post-COVID | -0.295* | -0.160 | 0.059 | -0.158 |
| | (0.118) | (0.115) | (0.802) | (0.814) |
| >1 day * COVID 1 | 0.036 | 0.007 | 1.486** | 1.164* |
| | (0.184) | (0.155) | (0.518) | (0.537) |
| >1 day * COVID 2 | 0.013 | 0.029 | 0.909 | 1.036 |
| | (0.171) | (0.127) | (0.529) | (0.559) |
| >1 day * Post-COVID | 0.036 | 0.055 | 1.294** | 1.351* |
| | (0.164) | (0.122) | (0.501) | (0.561) |

| Days WFH and COVID Period Interaction (cont.) | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Age respondent** | | 0.110* | | -0.455 |
| | | (0.049) | | (0.250) |
| **Live Together** | | -0.007 | | 0.511 |
| | | (0.194) | | (0.567) |
| **Children (0-4)** | | 1.299** | | 0.193 |
| | | (0.304) | | (0.590) |
| **Children (5-11)** | | 0.879** | | 0.582 |
| | | (0.248) | | (0.580) |
| **Children (12+)** | | 0.720** | | -0.111 |
| | | (0.263) | | (0.484) |
| **Part Days Childcare** | | 0.090 | | -0.145 |
| | | (0.046) | | (0.120) |
| **Commute Minutes** | | -0.004 | | 0.003 |
| | | (0.002) | | (0.007) |
| **Employment Sector** | | | | |
| Mining | | -0.178 | | |
| | | (0.338) | | |
| Industrial production | | 0.035 | | 3.458 |
| | | (0.320) | | (2.318) |
| Utilities production, distribution, and/or trade | | -0.631 | | 0.188 |
| | | (0.329) | | (3.163) |
| Construction | | -0.263 | | 2.379 |
| | | (0.205) | | (2.116) |
| Retail trade | | -0.344 | | 1.342 |
| | | (0.345) | | (2.160) |
| Catering | | -0.537 | | 2.819 |
| | | (0.293) | | (2.270) |
| Transport, storage, and communication | | -0.301 | | 0.690 |
| | | (0.222) | | (2.114) |
| Financial | | -0.319 | | 1.274 |
| | | (0.283) | | (2.935) |
| Business services | | 0.072 | | 3.509 |
| | | (0.260) | | (2.433) |
| Government services | | -0.413 | | 2.106 |
| | | (0.243) | | (2.075) |

| Days WFH and COVID Period Interaction (cont.) | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| Education | | -0.136 | | 4.021 |
| | | (0.319) | | (2.470) |
| Healthcare and welfare | | -0.145 | | 3.622 |
| | | (0.287) | | (2.142) |
| Environmental services, culture, recreation, and other services | | 0.701 | | 0.032 |
| | | (0.601) | | (2.306) |
| Other | | -0.426 | | 0.902 |
| | | (0.237) | | (2.020) |
| **Satisfaction Working Hours** | | -0.007 | | 0.010 |
| | | (0.016) | | (0.068) |
| **Household Division Index** | | 0.001 | | 0.042 |
| | | (0.016) | | (0.043) |
| **Care Division Index** | | 0.025 | | 0.105 |
| | | (0.031) | | (0.070) |
| **Intercept** | 0.010 | -5.321* | 2.667** | 19.101 |
| | (0.046) | (2.166) | (0.148) | (11.360) |
| **Number of observations** | 5307 | 5307 | 3314 | 3314 |

*Note.* This table provides the outcomes for regression of WFH Days on Hours Worked Less for Children. WFH stands for 'Work From Home'. Columns 1 and 2 present the outcomes for employees labeled full-time, columns 3 and 4 present the outcomes for employees labeled part-time. Standard errors are in parentheses. * p < .01, ** p < .05

# D Additional Analysis

## D.1 Hypothesis 1

**Table 23.** *FE Regression Results: Impact of WFH Hours on Hours Worked Across COVID Periods*

| | Hours Worked | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **WFH Hours** | 0.047 | 0.040 | 0.165 | 0.141 |
| | (0.058) | (0.059) | (0.089) | (0.086) |
| **COVID Period** | | | | |
| COVID 2 | -1.203 | -14.969* | -0.092 | 1.811 |
| | (0.827) | (7.208) | (0.592) | (1.823) |
| Post-COVID | -1.463* | -29.065* | 0.078 | 3.602 |
| | (0.734) | (14.232) | (0.551) | (3.406) |
| **WFH Hours * COVID Period** | | | | |
| WFH Hours * COVID 2 | -0.047 | -0.039 | -0.062 | -0.040 |
| | (0.061) | (0.061) | (0.078) | (0.076) |
| WFH Hours * Post-COVID | -0.017 | -0.004 | -0.145 | -0.120 |
| | (0.061) | (0.063) | (0.091) | (0.088) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 37.217** | -560.682 | 25.204** | 91.066 |
| | (0.480) | (310.375) | (0.382) | (75.019) |
| **Number of observations** | 3573 | 3573 | 2218 | 2218 |

*Note.* This table provides the outcomes for regression of WFH Hours on Hours Worked. WFH stands for 'Work From Home'. Columns 1 and 2 present the outcomes for employees labeled full-time, columns 3 and 4 present the outcomes for employees labeled part-time. Standard errors are in parentheses. * $p < .01$, ** $p < .05$

## D.2 Hypothesis 3a

**Table 24.** *FE Regression Results: Impact of WFH Hours on Working Less for Childcare Responsibilities*

| **Working Less for Children** | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **WFH Hours** | -0.001 | -0.001 | 0.001 | 0.001 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| **COVID Period** | | | | |
| COVID 2 | 0.005 | -0.089 | 0.007 | -0.071 |
| | (0.010) | (0.077) | (0.022) | (0.107) |
| Post-COVID | 0.005 | -0.176 | -0.003 | -0.164 |
| | (0.009) | (0.153) | (0.021) | (0.209) |
| **WFH Hours * COVID Period** | | | | |
| WFH Hours * COVID 2 | 0.000 | 0.000 | -0.003 | -0.002 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| WFH Hours * Post-COVID | 0.000 | 0.000 | -0.003 | -0.002 |
| | (0.001) | (0.001) | (0.002) | (0.002) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.026** | -3.862 | 0.174** | -3.527 |
| | (0.006) | (3.350) | (0.015) | (4.623) |
| **Number of observations** | 3573 | 3573 | 2218 | 2218 |

*Note.* This table provides the outcomes for regression of WFH Hours on Working Less for Children. WFH stands for 'Work From Home'. Columns 1 and 2 present the outcomes for employees labeled full-time, columns 3 and 4 present the outcomes for employees labeled part-time. Standard errors are in parentheses. * $p < .01$, ** $p < .05$

## D.3 Hypothesis 3b

**Table 25.** *FE Regression Results: Impact of WFH Hours on Hours Worked Less For Children Across COVID Periods*

| **Hours Less for Children** | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **WFH Hours** | -0.004 | -0.006 | -0.012 | -0.012 |
| | (0.005) | (0.005) | (0.023) | (0.024) |
| **COVID Period** | | | | |
| COVID 2 | 0.058 | -0.679 | 0.100 | 0.287 |
| | (0.092) | (0.616) | (0.268) | (1.342) |
| Post-COVID | 0.049 | -1.408 | -0.303 | 0.014 |
| | (0.090) | (1.224) | (0.253) | (2.555) |
| **WFH Hours * COVID Period** | | | | |
| WFH Hours * COVID 2 | 0.001 | 0.002 | -0.003 | 0.005 |
| | (0.006) | (0.005) | (0.021) | (0.021) |
| WFH Hours * Post-COVID | -0.000 | 0.001 | 0.007 | 0.016 |
| | (0.005) | (0.005) | (0.023) | (0.023) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.216** | -30.617 | 1.795** | 8.155 |
| | (0.061) | (26.657) | (0.168) | (57.213) |
| **Number of observations** | 3573 | 3573 | 2218 | 2218 |

*Note.* This table presents the fixed effects regression results of the impact of WFH Hours on Hours Less for Childcare across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.

# E Robustness check

## E.1 Hypothesis 1

**Table 26.** *FE Regression Results: Impact of WFH Days on Hours Worked Across COVID Periods*

| | Hours Worked | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | 1.870 | 1.802 | -5.446 | -5.056 |
| | (1.637) | (1.668) | (2.961) | (2.962) |
| 1 day | 3.778* | 3.748* | -1.679 | -2.105 |
| | (1.919) | (1.772) | (2.770) | (1.948) |
| >1 day | -1.334 | -1.220 | 4.286 | 4.492 |
| | (1.924) | (2.025) | (2.623) | (2.793) |
| **COVID Period** | | | | |
| COVID 2 | -1.775* | -15.666* | -0.062 | 1.983 |
| | (0.840) | (7.495) | (0.619) | (1.862) |
| Post-COVID | -1.417 | -29.353* | -0.165 | 3.646 |
| | (0.752) | (14.782) | (0.553) | (3.468) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 2 | -0.434 | -0.531 | 5.792* | 4.978 |
| | (2.920) | (2.944) | (2.860) | (2.759) |
| <1 day * Post-COVID | -2.216 | -2.249 | 1.989 | 1.454 |
| | (2.796) | (2.870) | (3.996) | (3.842) |
| 1 day * COVID 2 | 0.114 | -0.063 | -0.511 | 0.092 |
| | (2.244) | (2.077) | (2.156) | (1.709) |
| 1 day * Post-COVID | -1.115 | -1.234 | 1.358 | 1.916 |
| | (2.202) | (1.932) | (2.633) | (2.156) |
| >1 day * COVID 2 | 3.027 | 2.934 | -3.714 | -3.671 |
| | (2.031) | (2.112) | (2.623) | (2.690) |
| >1 day * Post-COVID | 2.288 | 2.429 | -5.178 | -5.174 |
| | (1.983) | (2.082) | (2.757) | (2.869) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 36.929** | -568.257 | 25.871** | 100.226 |
| | (0.523) | (321.363) | (0.391) | (76.066) |
| **Number of observations** | 3574 | 3574 | 2218 | 2218 |

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on Hours Worked across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.

## E.2 Hypothesis 3a

**Table 27.** *FE Regression Results: Impact of WFH Days on Working Less For Children Across COVID Periods*

| | Working Less for Children | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | 0.016 | 0.005 | 0.148 | 0.101 |
| | (0.017) | (0.018) | (0.104) | (0.103) |
| 1 day | 0.000 | -0.013 | 0.113 | 0.128 |
| | (0.027) | (0.025) | (0.074) | (0.075) |
| >1 day | 0.018 | 0.004 | 0.080 | 0.057 |
| | (0.036) | (0.034) | (0.075) | (0.056) |
| **COVID Period** | | | | |
| COVID 2 | 0.001 | -0.095 | 0.002 | -0.068 |
| | (0.009) | (0.078) | (0.022) | (0.101) |
| Post-COVID | 0.004 | -0.182 | 0.006 | -0.137 |
| | (0.009) | (0.155) | (0.022) | (0.196) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 2 | 0.039 | 0.050* | -0.147 | -0.098 |
| | (0.024) | (0.025) | (0.105) | (0.098) |
| <1 day * Post-COVID | -0.000 | 0.021 | -0.197 | -0.167 |
| | (0.016) | (0.018) | (0.120) | (0.119) |
| 1 day * COVID 2 | 0.012 | 0.016 | -0.044 | -0.048 |
| | (0.030) | (0.029) | (0.067) | (0.066) |
| 1 day * Post-COVID | 0.002 | 0.013 | -0.129 | -0.137 |
| | (0.027) | (0.025) | (0.079) | (0.081) |
| >1 day * COVID 2 | -0.019 | -0.006 | -0.040 | -0.002 |
| | (0.033) | (0.031) | (0.059) | (0.044) |
| >1 day * Post-COVID | -0.010 | -0.001 | -0.069 | -0.031 |
| | (0.032) | (0.031) | (0.058) | (0.044) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.021** | -3.894 | 0.158** | -3.129 |
| | (0.008) | (3.398) | (0.016) | (4.340) |

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on Working Less for Children across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.

## E.3 Hypothesis 3b

**Table 28.** *FE Regression Results: Impact of WFH Days on Hours Worked Less For Children Across COVID Periods*

| **Hours Less for Children** | | | | |
|---|---|---|---|---|
| | Full-time | Full-time | Part-time | Part-time |
| **Days WFH** | | | | |
| <1 day | 0.170 | 0.084 | 1.130 | 0.774 |
| | (0.122) | (0.123) | (0.846) | (0.831) |
| 1 day | 0.097 | 0.013 | 1.031 | 1.097 |
| | (0.208) | (0.191) | (0.605) | (0.634) |
| >1 day | 0.099 | 0.017 | 0.868 | 0.613 |
| | (0.254) | (0.233) | (0.638) | (0.535) |
| **COVID Period** | | | | |
| COVID 2 | 0.001 | -0.771 | -0.022 | 0.323 |
| | (0.082) | (0.627) | (0.275) | (1.303) |
| Post-COVID | 0.019 | -1.484 | -0.252 | 0.401 |
| | (0.107) | (1.250) | (0.262) | (2.460) |
| **Days WFH * COVID Period** | | | | |
| <1 day * COVID 2 | 0.342 | 0.461 | -1.279 | -0.891 |
| | (0.214) | (0.238) | (0.996) | (0.925) |
| <1 day * Post-COVID | 0.038 | 0.196 | -1.610 | -1.581 |
| | (0.135) | (0.153) | (1.318) | (1.325) |
| 1 day * COVID 2 | 0.107 | 0.158 | 0.479 | 0.508 |
| | (0.254) | (0.248) | (0.754) | (0.717) |
| 1 day * Post-COVID | -0.068 | 0.019 | -0.891 | -0.923 |
| | (0.205) | (0.192) | (0.691) | (0.728) |
| >1 day * COVID 2 | -0.036 | 0.057 | -0.182 | 0.205 |
| | (0.230) | (0.208) | (0.507) | (0.423) |
| >1 day * Post-COVID | -0.016 | 0.053 | -0.175 | 0.173 |
| | (0.237) | (0.219) | (0.484) | (0.434) |
| **Controls** | Not incl. | Incl. | Not incl. | Incl. |
| **Intercept** | 0.161* | -31.161 | 1.602** | 15.318 |
| | (0.072) | (27.200) | (0.186) | (55.109) |
| **Number of observations** | 3574 | 3574 | 2218 | 2218 |

*Note.* This table presents the fixed effects regression results of the impact of WFH Days on Hours Worked less for Children across different COVID periods. Columns 1 and 2 show the results for the full-time employees, while columns 3 and 4 present the results for part-time employees. Standard errors are in parentheses. * $p < 0.01$, ** $p < 0.05$.