

Does Work from Home Contribute to Increased BMI and Obesity? Evidence from Australian Data

Brenda Gannon* and Anastasia Semykina[†]

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Abstract

After the COVID-19 pandemic, work from home (WFH) became a viable and acceptable strategy to engage in the workforce. Reduced commute times can provide new opportunities to invest in health. However, the potential impact of WFH on a person's body weight received little attention in recent literature. We use data from the Household, Income and Labour Dynamics in Australia Survey to study the link between WFH arrangements and person's body mass index (BMI) and obesity. We find limited evidence of a systematic link between WFH and body weight measures, as most estimated effects are statistically insignificant. Significant positive effects are observed for full-time employees who worked 50 to 70% hours at home before the COVID-19 pandemic, but these effects are practically small, less than 1 kg of weight gain for a person of average height. Only about 0.5% of full-time workers have this type of WFH arrangement in the pre-COVID sample, indicating that positive effects are observed for a very small group of workers. Our exploration of potential mechanisms reveals notable differences in the nature of WFH before and after the pandemic. Observed time use patterns suggest that before COVID, employees with less than 70% of WFH had longer work hours and apparently had to take work home to complete tasks that they were unable to complete within regular work hours at the workplace. However, after the pandemic, there are no significant differences in work hours across different worker groups, and hybrid work arrangements provide more opportunities to balance work and home activities, including physically active tasks. Overall, our findings document no systematic relationship between worker body weight and WFH.

Keywords: BMI, obesity, work from home, hybrid work, time use

JEL Classification: I10, I12, J01, J22

*University of Queensland, School of Economics, St Lucia QLD 4067, Australia. Email: brenda.gannon@uq.edu.au. ORCID: 0000-0002-3672-4030

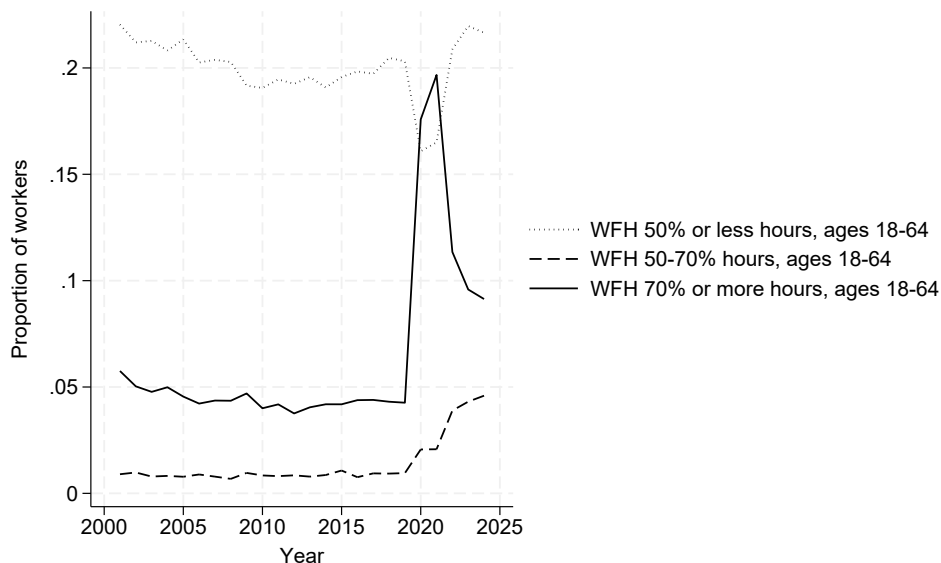
[†]Royal Melbourne Institute of Technology, School of Economics, Finance and Marketing, Melbourne VIC 3000, Australia. Email: anastasia.semykina@rmit.edu.au. ORCID: 0000-0001-7232-2971

This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Survey was initiated and is funded by the Australian Government Department of Social Services (DSS) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the authors and should not be attributed to the Australian Government, DSS or the Melbourne Institute. DOI 10.26193, <https://doi.org/10.26193/NBTNMTV>.

1 Introduction

As a by-product of the COVID-19 pandemic, the world had discovered work from home (WFH) as a viable and acceptable strategy to engage in the workforce. Even after the pandemic was officially over, all restrictions were lifted, and COVID-related health concerns substantially diminished, WFH persisted beyond the pre-pandemic levels (Cowan, 2024). In Australia, hybrid work arrangements were quite widespread even before the pandemic and have become more common in recent years. The data presented in Figure 1 show that in 2023-2024, the proportion of full-time employees working at least 70% hours at home was about 10%, twice as large as the corresponding proportion before COVID. Similarly, the proportion of full-time employees with 50% to 70% hours worked at home has been growing since the start of the pandemic and is now approaching 5%.

Figure 1: Proportion of Full-Time Employees, Ages 18-64, in Different WFH Arrangements.



Source: Authors' computations using HILDA data.

The benefits of WFH include better life-work balance and general well-being, reduced

work-to-family conflict, and higher levels of job satisfaction (Choudhury et al., 2024; Laß and Wooden, 2023; Laß et al., 2025; Lee, 2023, among others). Moreover, several studies document improved worker productivity under flexible work arrangements (Bloom et al., 2015; Choudhury et al., 2021; Angelici and Profetaatistics, 2024), which has led some to suggest that WFH could be a win-win for employers and employees. However, the health implications of WFH are not yet fully understood. Several recent studies consider the link between WFH and mental health before and during the COVID-19 pandemic (Bilgrami, 2023; Hao et al., 2022; Sung et al., 2024; Botha et al., 2026). The impact of WFH on physical health received less attention in recent literature, despite being potentially important. The freed-up time from a decreased commute opens the possibility of devoting more attention to health, increasing the frequency of exercise and cooking meals at home. On the other hand, the sedentary nature of most jobs done from home may result in less physical activity and unhealthy lifestyle choices. The present paper studies the effect of WFH on two health-related outcomes – body mass index (BMI) and obesity.¹ Given the large share of jobs with WFH arrangements in Australia, it is important to learn more about the relationship between WFH and body weight.

A starting point to develop our hypothesis is to reflect on the familiar Grossman (1972) model, which denotes health as a consumption and investment good. An output such as health, depends on market goods and the utility trade-off between leisure and working, all subject to constraints of budget and time available. Health outcomes will depend on the marginal productivity of inputs, e.g. if WFH is a good investment, then health will improve through the channels of increased time for work-life balance. If not, then we may see a disimprovement in health outcomes, if isolation occurs or there is less focus on healthy behaviours such as exercise and diet. Individuals may even reduce their

¹Following the definition adopted by the World Health Organization (<https://www.who.int/news-room/fact-sheets/detail/obesity-and-overweight>), BMI is defined as weight in kilograms divided by height in meters squared; obesity corresponds to BMI being greater than or equal to 30.

time spent working, if they feel less healthy.

We explore the relationship between WFH and workers' body weight using data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. HILDA is an ongoing longitudinal survey of Australian households and has several characteristics that make it exceptionally well-suited for this study. While most previous studies of body weight and obesity use cross section data, HILDA is a panel that follows respondents over time and contains records of self-reported weight and height since 2006. Information about hours worked from home has been collected since the inception of HILDA Survey in 2001. Moreover, data on physical activity and time use are collected annually, and diet questions were included in selected waves of the survey. This information allows us to study potential mechanisms underlying the relationship between WFH and weight.

Estimation is performed for pre-COVID (years 2006-2019) and post-COVID (2022-2024) periods to assess the net effect of WFH on body weight separate from the impact of the pandemic and lockdown. We use the two-way fixed effects linear model, which accounts for common time factors and unobserved individual characteristics, such as genetics, chronic health conditions, and family background. We also exploit the rich content of HILDA data to control for recent health shocks, such as personal injury and serious disease. Estimated effects of WFH are statistically insignificant in most regressions. Positive significant effects are found only before the COVID-19 pandemic, where the intermediate WFH intensity (50 to 70% hours worked at home) is associated with higher probability of obesity among women and increased BMI among both male and female employees. However, the effects are practically small and correspond to a modest increase in weight of less than 1 kilogram. The results are robust to small changes in the definitions of WFH variables, accounting for past WFH effects, and correcting for potential sample selection bias. Additional analysis suggests that reverse causality is unlikely.

To improve understanding of the underlying mechanisms, we study the link between

WFH and physical activity, time use, and diet using the two-way fixed effects analysis. We find that before COVID, respondents with low WFH (50% or less hours) spent more time on commute than respondents working only in the office. Moreover, employees with low and intermediate WFH arrangements tended to have longer work hours than respondents with zero or high WFH (70% or more hours). In contrast, after COVID there are no significant differences in work hours across different types of work arrangements, but hybrid work is linked to more time spent on physically active home tasks compared to zero WFH.

This study contributes to the large literature on the economics of obesity. Although there is much evidence on the costs involved (Black et al., 2018; Cawley and Meyerhoefer, 2012; Ling et al., 2023; Doherty et al., 2017), there has been less evidence on the determinants of obesity and BMI (see Cawley (2015) for a review) or on the impacts of the pandemic on BMI (Sung et al., 2024). Since Cawley (2015), there have been some further studies. James et al. (2020) find that genetics and family environment substantially contribute to the persistence of BMI between generations. DiNardi et al. (2019) and Michelle et al. (2024) document the positive effects of internet access on body weight and obesity. Srivastava et al. (2024) find that parental smoking is associated with higher risk of obesity in children. Sung et al. (2024) and Scoditti et al. (2024) use cross section data to document a significant increase in body weight shortly after the COVID-19 lockdown, when restrictions on physical mobility and fear of infection through social interaction likely played an important role. Our study adds to this literature by focusing on the socioeconomic impacts of WFH outside of the COVID-19 pandemic period, when body weight outcomes are determined by individual choices rather than externally imposed restrictions or serious health concerns.

The present paper also contributes to the growing literature on WFH. The pre-pandemic literature explores associations between the extent of telecommuting and work

outcomes, such as worker organizational commitment, turnover intentions, and job satisfaction. For a review, see Allen et al. (2015). More recent literature includes studies of WFH trends and WFH impact on productivity, mentoring, and organizational performance (Abrardi et al., 2024; Barrero et al., 2023; Aksoy et al., 2022; Emanuel et al., 2023), as well as time use Aksoy et al. (2023); Cowan (2024). In terms of health, the pre-pandemic studies of telework and mental health produce mixed results (Furuya et al., 2022). When considering the COVID-19 pandemic period, Hao et al. (2022) and Bilgrami (2023) find that WFH is associated with worsening mental health, likely due in part to concerns of getting infected (Serrano-Alarcón et al. (2022)). In contrast, Amerikaner et al. (2023) report an improvement in the emotional well-being of sexual and gender minorities working at home during lockdown. Similarly, Botha et al. (2026) find positive pre-COVID effects of WFH on mental health of women with poor levels of mental health when the WFH component is sizable. As mentioned earlier, existing literature that examines the link between individual body weight and WFH typically focuses on the analysis of cross section data and considers COVID-19 pandemic (Sung et al., 2024; Scoditti et al., 2024). To the best of our knowledge, there are no studies exploring such a relationship before or after the pandemic. We extend the literature by examining the outcomes outside of the COVID-19 pandemic, as well as using longitudinal survey data and panel-data methods to study the link between WFH and health-related outcomes – BMI and obesity.

2 Conceptual Framework

As noted by Cawley (2015), body weight can vary due to two components: calorie intake and calorie expenditure. WFH may contribute to both of these factors. According to Grossman (1972) model, individuals can allocate the additional time afforded by hybrid work between investing in health and producing other commodities, which require both

time and market goods as inputs. Individuals with higher marginal utility of health might welcome additional opportunities to engage in formal exercise and training, e.g. signing up for a fitness class or joining a sports club. WFH and reduced commute may also endow individuals with the additional time and flexibility of interchanging work done for pay with household routine tasks and producing household commodities, such as clean house, meals cooked at home, and playing with children. Such flexibility may be especially appreciated by women, who tend to shoulder the majority of the housework. As long as the housework tasks involve standing and moving, they can facilitate more calorie burning throughout the day since work-related physical activity can reduce the BMI of adults in the range of 0.2 to 0.4 points (Sarma et al., 2014). For example, compared to those who are inactive at work in their usual daily activity, being able to stand or walk at work reduces BMI by approximately 0.17 points in men and 0.30 points in women (Sarma et al., 2014). On the other hand, WFH reduces the necessity to leave the house, which can lead to less physical activity among individuals who choose not to invest in health.

Aksoy et al. (2023) and Cowan (2024) document significant time savings as a consequence of higher WFH levels and decreased commute shortly after the pandemic - a trend common to 27 countries. They find that the extra time was spent on childcare and caring for other relatives, but not on physical exercise. Hence, the implications for body weight are unclear.

Regarding calorie consumption, the impact of WFH can similarly be either beneficial or harmful. If WFH motivates health investments in the form of cooking meals at home, it can lead to a healthier diet and lower body weight (Restrepo and Zeballos, 2020; Strupat et al., 2021). On the other hand, if WFH increases the frequency of ordering home delivery meals due to the higher value of restaurant food under the existing time constraint, it may have an adverse effect. Using the Behavioral Risk Factor Surveillance System data, Sung et al. (2024) find a significant increase in the BMI two months after

the COVID-19 lockdown. As possible mechanisms they discuss the lockdown impact on mental health, sedentary lifestyle and diet choice. They find that Google searches for food delivery services and high-calorie foods have increased post the lockdown. O’Connell et al. (2022) employ a representative panel of British households to investigate the impact of the COVID-19 pandemic on calorie consumption and find an increase in calorie intake due to more calories consumed at home.

Whether WFH is associated with higher health investments is an empirical question. We attempt to answer it in Section 5.

3 Data

The analysis is performed using data from the HILDA Survey, a nationally representative longitudinal survey of Australian households, which contains detailed information on family and individual social, economic, health and wellbeing measures. The data have been collected annually since 2001 with interviews conducted from August of a given year to February of the following year; for example, wave 1 data collection occurred from August 2001 to February 2002.² Because weight and height records are not available before wave 6, we use waves 6-19 (pre-pandemic period) and 22-24 (post-pandemic period). The analysis is conducted by period to explore changes over time. Australia’s last lockdown was in 2021, following the outbreak of the SARS-CoV-2 Delta variant. By December 2021, 90% of the population had been vaccinated and most public health restrictions were lifted. Forced lockdowns and fear of being infected during the pandemic had a significant impact on individual behaviours and obscured the link between WFH and individual choices and outcomes. Therefore, we exclude waves 20 and 21, so that the period from March 2020 to July 2022 is not included in the analysis.

²For more information about the design of HILDA see Watson and Wooden (2012).

Sample. Because the goal is to study the effect of working arrangements, we follow the labor economics literature and conduct the main analysis using the sample of full-time employees working between 35 and 70 hours per week, ages 18-64. When studying heterogeneous effects, separate estimation is performed for part-time employees, who tend to have different characteristics and outcomes than full-time workers (Been et al. (2026) and references therein). Military servicemen and servicewomen, workers in agricultural jobs, self-employed, full-time students, and individuals whose BMI exceeds 45 or is less than 17 are excluded. In the HILDA Survey, WFH variables are only available for the main job; therefore, respondents who have multiple jobs are excluded. Moreover, observations with missing values for any of the explanatory variables used in the analysis are removed. Table 10 in the Appendix contains information on the number of observations excluded due to various reasons. Almost 70% of the observations are dropped due to age restrictions, missing BMI or not working. Another 5% are excluded because the respondent is a full-time student, self-employed or holds multiple jobs. The final sample for full-time workers is comprised of 79,488 observations for 15,827 individuals. The sample for part-time employees consists of 31,403 observations for 9,543 individuals.

Body weight and WFH variables. As health and health-related outcomes, we consider two measures: a person’s BMI (defined as weight in kilograms divided by height in meters squared) and an indicator for being obese ($BMI \geq 30$). Because height and weight are self-reported, BMI is likely to contain a measurement error. Although our estimation strategy partially addresses this issue, some concerns may still remain. We discuss this in detail in Section 4.1.

WFH variables are created using the fraction of time worked from home - a ratio of weekly hours usually worked at home for the main job and total weekly hours usually worked in the main job. Because previous studies find non-linear effects of WFH on other outcomes (Choudhury et al., 2024; Botha et al., 2026), we create WFH categories instead

of using a linear measure. Similar to Choudhury et al. (2024), we construct indicators for low WFH (50% or less of weekly hours worked at home), intermediate WFH (between 50% and 70% worked at home), and high WFH (70% or more worked at home).³ Percentages are used instead of the number of days because the number of days worked at home is not available until 2023, and the data reveal no clear pattern in the fraction of WFH hours that could suggest a link to the number of days. The categories are called “low,” “intermediate,” and “high” for convenience and reflect differences across the groups rather than practical importance of WFH allocation for a given group. The cutoff points for each WFH category were determined using a data-driven process described in Section 4.1.

Physical activity and time-use variables. As part of the HILDA Survey, all respondents are asked to fill out a Self-Completion Questionnaire, which includes a question: “In general, how often do you participate in moderate or intensive physical activity for at least 30 minutes?” Possible responses take on six values ranging from 1 = “Not at all” to 6 = “Every day.” We call the corresponding variable physical activity.

The Self-Completion Questionnaire also asks about the number of hours and minutes typically spent per week on different activities. We consider five types of activities: (i) commute (travelling to/from paid employment), (ii) household errands (e.g. shopping, banking, paying bills, and keeping financial records), (iii) housework (preparing meals, washing dishes, cleaning house, washing clothes, ironing and sewing, etc.), (iv) outdoor tasks (home maintenance, such as repairs, improvements, painting, etc., car maintenance or repairs, and gardening), and (v) childcare (playing with own children, helping them with personal care, teaching, coaching or actively supervising them, or getting them to child care, school and other activities).

Diet variables. Diet-related questions are included in the Self-Completion Questionnaire in waves 7, 9, 13, and 17 of the survey. Specifically, the question asks “How

³Choudhury et al. (2024) collect data differently and use the number of WFH days in their variable definitions.

often do you usually eat each of the following food types?” with possible answers ranging from 1 = “Never” to 8 = “Two or more times per day.” We examine consumption of the following food types that are generally considered unhealthy and may contribute to weight gain: (i) baked goods (biscuits, cakes, pies, cake-type desserts, pastries, etc), (ii) snack foods, (iii) confectionery and ice cream, (iv) bread products (breads, crumpets and English muffins), (v) hot chips (fried potatoes, french fries, hot chips or wedges), (vi) processed meat products. Diet variables are not available in the post-COVID period.

Data Description Summary statistics for the sample of full-time employees are presented in Table 1. Similar to other high-income countries, obesity is a serious problem in Australia. The average BMI in the sample is almost 27 in 2006-2019 and is higher after the pandemic. The prevalence of obesity rose by nearly 6 percentage points between the pre- and post-COVID periods. BMI also increased over time, although it declined in the most recent wave of the survey for both women and men (Figure 2 in the Appendix).

WFH is reasonably common in the sample. Almost 24% of respondents did some work at home before the pandemic. Shortly after the pandemic, the proportion of respondents with nonzero WHF increased to over 40%, which is largely due to the greater share of respondents working more than 50% hours from home. Densities for WFH among individuals with nonzero WFH, physical activity, time use, and diet variables before and after COVID are included in the Supplementary Information file.

4 Effects of WFH on BMI and Obesity

4.1 Empirical Strategy

To examine the impact of WFH on body weight and obesity, we follow Botha et al. (2026) and estimate a linear two-way fixed effects model that accounts for time and individual-

Table 1: Summary Statistics (Full-Time Workers)

Variable	Pre-COVID			Post-COVID		
	N	Mean	SD	N	Mean	SD
	(1)	(2)	(3)	(4)	(5)	(6)
BMI	64,469	26.897	4.852	15,019	27.684	5.297
Obese	64,469	0.231	0.421	15,019	0.288	0.453
No WFH	64,469	0.762	0.426	15,019	0.594	0.491
Low WFH	64,469	0.218	0.413	15,019	0.257	0.437
Intermediate WFH	64,469	0.005	0.071	15,019	0.056	0.229
High WFH	64,469	0.014	0.118	15,019	0.094	0.291
Age (years)	64,469	40.024	12.029	15,019	40.594	11.812
Female	64,469	0.381	0.486	15,019	0.414	0.493
Years of schooling (pre-tertiary)	64,469	11.327	1.017	15,019	11.528	0.890
Completed secondary education	64,469	0.145	0.352	15,019	0.140	0.347
Graduate education	64,469	0.150	0.357	15,019	0.196	0.397
Bachelor or honours degree	64,469	0.200	0.400	15,019	0.232	0.422
Diploma or advanced diploma	64,469	0.106	0.308	15,019	0.098	0.297
Certificate III or IV	64,469	0.253	0.434	15,019	0.241	0.427
Experience (years)	64,469	20.383	11.859	15,019	20.396	11.555
Work hours on main job	64,469	43.420	7.222	15,019	42.286	6.523
Per capita household income (\$1,000 AUD)	64,469	39.699	29.989	15,019	43.344	37.154
Married	64,469	0.707	0.455	15,019	0.710	0.454
Pregnant in last 12 months	64,456	0.020	0.140	15,016	0.027	0.163
Serious injury or illness in last 12 months	64,469	0.063	0.243	15,019	0.062	0.241
Has long-term health condition	64,469	0.143	0.350	15,019	0.159	0.366
Long-term health condition limits work	64,469	0.061	0.239	15,019	0.070	0.256
Changed job since last interview	64,469	0.196	0.397	15,019	0.210	0.407
Changed address since last interview	64,469	0.169	0.375	15,019	0.154	0.361
Physical activity	64,349	3.668	1.474	15,010	3.657	1.479
<i>Time use</i>						
Commute	63,111	4.971	4.160	14,697	4.376	4.264
Errands	63,161	3.586	3.581	14,812	3.712	3.926
Housework	63,725	7.475	6.648	14,879	7.552	6.791
Outdoor tasks	63,135	3.410	4.568	14,821	3.025	4.106
Childcare	63,624	4.988	10.255	14,879	5.976	11.809
Paid employment	63,867	43.057	9.164	14,856	41.758	9.451
<i>Diet</i>						
Baked goods	17,547	4.309	1.460			
Snack foods	17,528	3.963	1.388			
Confectionery and ice cream	17,535	4.165	1.475			
Bread products	17,548	5.619	1.530			
Hot chips	17,522	3.544	1.186			
Processed meat products	17,550	4.005	1.348			

Note: Detailed description of the variables is provided in Section 3.

home-job fixed effects. The estimated equation is:

$$y_{it} = \theta_t + \beta_1 lowWFH_{it} + \beta_2 intermWFH_{it} + \beta_3 highWFH_{it} + \gamma' X_{it} + c_i + u_{it}, \quad (1)$$

where i is a unique individual-home-job spell, θ_t includes wave indicators, while $lowWFH_{it}$, $intermWFH_{it}$, and $highWFH_{it}$ are the WFH indicators corresponding to the three levels of WFH intensity described in Section 3 (the reference category is zero WFH). Variables in X_{it} are the variants of standard controls typically used in the analysis of BMI and obesity (see, for example, Ampofo et al. (2025), Chou et al. (2004), DiNardi et al. (2019)): age indicators,⁴ years of schooling (the highest grade of secondary education completed), indicators for completed secondary education and post-secondary degrees, real annual per capita household income measured in 2000 Australian dollars, marital status indicator equal to one for individuals who are either formally married or have a partner, and state indicators. To account for long-term health issues, adverse health shocks and variation in work responsibilities, all regressions include indicators for having a long-term health condition, whether the condition limits work, indicator for respondent reporting a serious personal injury or illness during the last 12 months, and occupation fixed effects. For women reporting pregnancy during the last 12 months, indicators for pregnancy starting 0-3 months ago, 4-6 months ago, 7-9 months ago, and 10-12 months ago were created and incorporated as covariates. The individual-home-job fixed effect c_i accounts for unobserved time-constant factors, such as genetics, chronic health conditions, and family background, as well as unique characteristics of the job and place of residence. We consider two outcomes (y_{it}) - the person's BMI and indicator for being obese - and adjust standard errors for clustering at the individual level.

As a robustness check, we re-estimated the model using a sample that excluded preg-

⁴Indicators for 5-year age intervals were included: age between 20-24 years, 25-29 years, ..., 60-64 years. The reference group is 18-19 years old.

nant women and sample that omitted respondents reporting recent injury or illness (results are reported in the Appendix). Moreover, we re-estimated the models that included different children variables (number of children ages 0-14 years old, number of children ages 0-4 years old, an indicator for having children under 5 years old), models that included age and age squared instead of age indicators, and models that used $\log(\text{income})$ or $\log(\text{wage})$ instead of the income variable. In all cases, the estimated effects of WFH were similar to the main results.⁵

Reverse causality. In the analysis of health outcomes, concerns may arise because individual choices (e.g. WFH arrangements) may depend on person’s health. Including individual-job-home fixed effects helps alleviate this concern, as this method controls for unobserved individual-specific characteristics, including genetics and the presence of time-invariant chronic health conditions. In model (1), the identification relies on the within-person variation in WFH and body weight over time. Specifically, the estimated effects capture the expected changes in the measures of body weight based on the changes in person’s WFH arrangements. A key identifying assumption is that idiosyncratic shocks to BMI and obesity do not affect the percent of hours worked at home. While the violation of this assumption is unlikely, there may be cases when a time-specific shock to person’s health may influence both BMI and WFH. To mitigate potential distortions, individual-job-home fixed effects and indicators for a long-term health condition, recent serious injury/illness, and pregnancy are included in all regressions. Furthermore, when analyzing results, we consider other evidence to evaluate whether reverse causality may be present.

Measurement error. Another common concern is the measurement error in the BMI variable. In the HILDA survey, both height and weight are self-reported and may not be very accurate (Wooden et al., 2008). Classical measurement error in the dependent

⁵Detailed results are available from the authors upon request.

variable leads to larger standard errors, but does not induce bias (Wooldridge, 2010). However, if the measurement error is not classical and is correlated with explanatory variables, it may cause bias. In our estimation, the time-constant component of the measurement error is absorbed by individual fixed effects. To ensure that the time-varying component does not create bias, we have to assume that the discrepancies in measurement error over time are not systematically related to WFH variables. For example, respondents working only in the office should not start overstating their weight once they switch to the intermediate WFH. If misreporting occurs, it is assumed to be stable over time, and any time deviations are assumed to be random.

The measurement error in WFH variables is also important to consider. To define low, intermediate, and high WFH indicators mentioned above, we estimated a flexible specification of equation (1), which included indicators for each decile of the fraction of hours worked at home. Then, the deciles with similar effects were grouped into larger units to avoid multicollinearity and increase the number of observations within each group. In what follows, we perform a robustness check, where the model is estimated using slightly different definitions of WFH variables to assess the sensitivity of results.

Effects of past WFH. Equation (1) includes contemporaneous measures of WFH and body weight. One might ask whether past WFH experiences have additional effects on BMI and obesity and should be included. Given that body weight can change reasonably quickly, we expect the contemporaneous effects to be the strongest. However, as a robustness check we estimate an extended version of equation (1), which includes previous-year WFH arrangements as additional covariates. This specification allows us to check whether WFH may have lasting effects, so that the potential weight gain/loss may accumulate over time or persist after returning to office.

Sample selection. When estimating the effects of WFH, only working individuals can be included in the analysis, which raises the issue of sample selection. Missing values in

explanatory variables (in our case WFH indicators) are typically assumed to be unrelated to the dependent variable, thus causing inefficiency but not bias (Abrevaya and Donald, 2017). This assumption may not be valid in the case of body weight, as the weight loss was found to improve the chances of employment, particularly among obese women (Reichert, 2015).

To address this problem, we test for nonrandom selection and perform the correction as a robustness check using a two-step procedure. First, we define a selection indicator s_{it} equal to one if the respondent is 18-64 years old, works between 35 and 70 hours per week in a single non-agricultural job, is not self-employed and is not a full-time student (i.e. included in WFH analysis). The selection indicator is set to zero for all other respondents who are 18-64 years old.⁶ The selection equation is estimated using the fixed-effects logit model:

$$P(s_{it} = 1) = \Lambda(\delta' Z_{it} + \alpha_i) = \frac{\exp(\delta' Z_{it} + \alpha_i)}{1 + \exp(\delta' Z_{it} + \alpha_i)}, \quad (2)$$

where Z_{it} includes wave indicators, variables X_{it} from equation (1), years of experience and years of experience squared. Estimation relies on the assumption that work experience impacts the probability of working but has no direct effect on body weight after accounting for age and other covariates. Individual fixed effects α_i capture unobserved factors, such as innate ability and cultural background. WFH variables, job changes, and occupation fixed effects could not be included because they are not observed for respondents who do not work.

Estimated coefficients from model (2) are used to compute the predicted probability of selection, $\hat{\Lambda}_{it} = \Lambda(\hat{\delta}' Z_{it})$, where α_i is set to zero (its expected value). Because the selection equation is estimated using the logit model, testing and correction methods that rely on normal error distribution, e.g. Wooldridge (1995), cannot be used. Instead, we employ a semiparametric series estimator to correct for selection (Newey, 2009; Semykina

⁶Respondents whose BMI is less than 17, greater than 45, or is missing are excluded from both groups.

and Wooldridge, 2010). Specifically, we estimate

$$\begin{aligned}
y_{it} = & \theta_t + \beta_1 lowWFH_{it} + \beta_2 intermWFH_{it} + \beta_3 highWFH_{it} \\
& + \gamma' X_{it} + \rho_1 \hat{\Lambda}_{it} + \rho_2 \hat{\Lambda}_{it}^2 + \rho_3 \hat{\Lambda}_{it}^3 + c_i + u_{it}.
\end{aligned} \tag{3}$$

This equation uses the same variables as model (1), and also includes correction terms $\hat{\Lambda}_{it}$, $\hat{\Lambda}_{it}^2$, and $\hat{\Lambda}_{it}^3$ that capture the impact of selection. If ρ_1 , ρ_2 , and ρ_3 all equal zero, it would indicate no sample selection bias. However, if at least one of these coefficients is different from zero, it would be evidence of nonrandom selection. Model (3) can also be used to obtain the unbiased estimates of WFH effects under the assumption that conditional on the individual fixed effect, an idiosyncratic shock to person's BMI has only a contemporaneous effect on employment. We use equation (3) to both test and correct for selection.

4.2 Main Effects

The estimated effects of WFH are displayed in Table 2. It is evident that during the pre-COVID period, the effect of WFH is not linear. There are no significant BMI differences between individuals working only from the office and those on low- and high-intensity WFH schedules. The same is true for the probability of being obese. However, having an intermediate WFH intensity is associated with a 0.27 higher BMI and 4.1 percentage points higher probability of being obese before the pandemic. The nonlinearity finding is similar to Choudhury et al. (2024), who find that the intermediate WFH has stronger effects on worker productivity than low and high WFH arrangements. Importantly, non-linear WFH effects are inconsistent with the reserve causality argument, as more hours of WFH should be preferred if having a medical condition causing a weight gain, and this is not what we observe.

In contrast, WFH has no systematic effects on either measure of the body weight during the post-pandemic period. The coefficients on the WFH variables are small and statistically insignificant in columns (3) and (4).

Table 2: Estimated Effects of WFH on BMI and Obesity, Whole Sample				
	Pre-COVID		Post-COVID	
	(1)	(2)	(3)	(4)
Low WFH	0.029 (0.028)	0.005 (0.004)	0.047 (0.062)	-0.002 (0.009)
Intermediate WFH	0.268** (0.115)	0.041** (0.019)	0.007 (0.102)	0.002 (0.015)
High WFH	0.070 (0.093)	0.018 (0.014)	0.105 (0.113)	0.008 (0.018)
Observations	64,469	64,469	15,019	15,019

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** statistically significant at the 1%, ** 5%, * 10%.

4.3 Heterogeneity and Robustness Checks

In this Section, we study heterogeneous effects by gender, occupation, and part-time work status.⁷ Dingel and Neiman (2020) use the Occupational Information Network survey data to assess how many jobs can be done entirely at home. They find that at least some jobs in most occupations can be performed from home, but such jobs are most commonly found in computer, education, legal, business/financial, and management occupations. Importantly, many of these jobs tend to be sedentary, which can have implications for

⁷We also conducted the analysis separately for younger and older workers and found no significant differences by age.

health, including body weight. The two types of jobs considered in this paper are office jobs (legislators, managers, and clerks) and all other jobs.⁸ Employees in office jobs are expected to be at a higher risk of physically inactive lifestyles and excess weight. Analysis by gender and part-time status is warranted because the behavior and work schedules tend to be different for men and women, and for part-time employees.

4.3.1 Gender Heterogeneity

Gender-specific estimates in Table 3 indicate notable differences between women and men. During the pre-pandemic period, the estimated effect of intermediate WFH on BMI for women is 0.34 and statistically significant at the 10% significance level. For a woman of average height (about 165 cm), it implies approximately 0.93 kg greater weight if the woman has an intermediate WFH work schedule compared to a woman who works 100% of the time from the office. The corresponding difference in the probability of being obese is 10.9 percentage points. The impact of WFH on men’s body weight is less pronounced. For a man of average height (178 cm), intermediate WFH intensity is associated with an increase in weight of approximately 0.73 kg (0.23 increase in BMI), and the estimated effect of low WFH is much smaller. WFH has no effect on the likelihood of obesity among men. Consistent with the estimates obtained for the whole sample, all WFH variables are insignificant after COVID (columns (3) and (4), Table 3).

To check the robustness of these findings, we re-ran the regressions after excluding pregnant women and respondents reporting injury or serious illness within the last 12 months. The results are reported in Tables 11 and 12 in the Appendix and are similar to the estimates in Tables 2 and 3.

⁸It was not possible to fully match the occupations with Dingel and Neiman (2020) because of the differences in occupation codes across surveys. Moreover, office jobs in our classification exclude professionals, such as school teachers and health associates.

Table 3: Estimated Effects of WFH on BMI and Obesity by Gender

	Pre-COVID		Post-COVID	
	BMI (1)	Obese (2)	BMI (3)	Obese (4)
<i>Women</i>				
Low WFH	-0.033 (0.050)	0.001 (0.006)	0.037 (0.118)	0.008 (0.011)
Intermediate WFH	0.343* (0.208)	0.109*** (0.035)	-0.038 (0.179)	-0.006 (0.020)
High WFH	0.069 (0.167)	0.017 (0.018)	0.170 (0.190)	0.026 (0.025)
Observations	24,584	24,584	6,215	6,215
<i>Men</i>				
Low WFH	0.067** (0.033)	0.007 (0.005)	0.064 (0.068)	-0.007 (0.013)
Intermediate WFH	0.232* (0.139)	0.006 (0.021)	0.033 (0.116)	0.012 (0.021)
High WFH	0.078 (0.111)	0.019 (0.019)	0.032 (0.136)	-0.012 (0.026)
Observations	39,885	39,885	8,804	8,804

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** statistically significant at the 1%, ** 5%, * 10%.

4.3.2 Part-Time Workers

The estimated effects of WFH on BMI and obesity for part-time employees are displayed in Table 4. Analogous to full-time workers, WFH has no significant effect on BMI and obesity of part-time workers after the COVID-19 pandemic. During the pre-COVID

Table 4: Estimated Effects of WFH on BMI and Obesity, Part-Time Workers

	Pre-COVID		Post-COVID	
	BMI	Obese	BMI	Obese
	(1)	(2)	(3)	(4)
<i>Whole sample</i>				
Low WFH	0.013 (0.060)	-0.014* (0.007)	0.228 (0.171)	0.026 (0.023)
Intermediate WFH	0.044 (0.174)	-0.011 (0.021)	0.312 (0.271)	-0.006 (0.027)
High WFH	0.062 (0.122)	-0.018 (0.015)	0.008 (0.242)	-0.007 (0.030)
Observations	22,599	22,599	5,142	5,142
<i>Women</i>				
Low WFH	0.054 (0.064)	-0.009 (0.008)	0.237 (0.188)	0.016 (0.024)
Intermediate WFH	0.083 (0.185)	0.002 (0.024)	0.293 (0.312)	-0.016 (0.031)
High WFH	0.138 (0.140)	-0.020 (0.017)	-0.016 (0.272)	-0.015 (0.034)
Observations	17,977	17,977	4,024	4,024
<i>Men</i>				
Low WFH	-0.294* (0.164)	-0.049** (0.024)	0.000 (0.410)	0.102 (0.076)
Intermediate WFH	-0.184 (0.408)	-0.059 (0.044)	0.053 (0.450)	0.054 (0.064)
High WFH	-0.144 (0.243)	-0.014 (0.032)	0.130 (0.475)	0.010 (0.081)
Observations	4,622	4,622	1,118	1,118

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** statistically significant at the 1%, ** 5%, * 10%.

period, working 50% or less hours at home is associated with lower BMI and reduced risk of obesity for men. The direction of the effects is the opposite to that for full-time employees, which is likely due to differences in work hours and corresponding time constraints faced by these two groups of workers. Part-time employees work on average about 22 hours per week, which implies limited impact of employment on daily lives and non-work activities of these individuals.

4.3.3 Occupation Heterogeneity

The WFH effects for workers in office and other jobs are presented in Table 5. Given the notable differences by gender, the estimation is done separately for women and men.

The effects of WFH are only significant for women before the COVID pandemic. As expected, the estimated effect of the intermediate WFH on the likelihood of obesity is higher for women in office jobs (15 percentage points increase) than for women in other jobs (8 percentage points increase). However, there are no significant effects for women in office or other jobs after the pandemic. Furthermore, there are no systematic effects of WFH on body weight outcomes for men in either type of job or time period, which may be due to smaller sample sizes and reduced efficiency.

Table 5: Estimated Effects of WFH on BMI and Obesity by Occupation and Gender

	Office jobs				Other jobs			
	Pre-COVID		Post-COVID		Pre-COVID		Post-COVID	
	BMI (1)	Obese (2)	BMI (3)	obese (4)	BMI (5)	Obese (6)	BMI (7)	Obese (8)
<i>Women</i>								
Low WFH	-0.002 (0.088)	0.026** (0.011)	0.152 (0.220)	0.015 (0.019)	-0.027 (0.062)	-0.008 (0.007)	-0.016 (0.154)	0.009 (0.013)
Intermediate WFH	0.659 (0.423)	0.150** (0.066)	0.031 (0.305)	0.002 (0.030)	0.152 (0.226)	0.081** (0.040)	-0.057 (0.249)	-0.011 (0.029)
High WFH	0.180 (0.296)	0.052 (0.031)	0.489 (0.328)	0.045 (0.038)	-0.011 (0.204)	-0.004 (0.021)	0.179 (0.279)	0.027 (0.041)
Observations	8,500	8,500	2,059	2,059	16,084	16,084	4,156	4,156
<i>Men</i>								
Low WFH	0.065 (0.056)	0.009 (0.009)	-0.019 (0.107)	0.003 (0.027)	0.053 (0.043)	0.007 (0.006)	0.126 (0.094)	-0.019 (0.016)
Intermediate WFH	0.113 (0.257)	-0.010 (0.040)	-0.089 (0.175)	0.023 (0.042)	0.216 (0.153)	0.033 (0.023)	0.142 (0.167)	0.034 (0.025)
High WFH	-0.108 (0.255)	0.029 (0.053)	-0.182 (0.244)	0.007 (0.056)	0.205 (0.143)	0.031 (0.023)	0.275 (0.202)	-0.001 (0.035)
Observations	10,091	10,091	2,296	2,296	29,794	29,794	6,508	6,508

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects. *** statistically significant at the 1%, ** 5%, * 10%.

4.3.4 Robustness Checks

Alternative variable definitions. As discussed in Section 4.1, we explore how the estimated effects of WFH on body weight measures change when the definition of WFH variables is modified. Table 13 in the Appendix displays the estimates obtained by re-defining the intermediate WFH indicator to equal one if working 45% to 75% hours at home. The low and high WFH indicators are adjusted accordingly. The results are similar to those in Tables 2 and 3. When re-defining the intermediate WFH indicator to equal one if working 55% to 65% hours at home, the results are also qualitatively unchanged (Table 14 in the Appendix).

Effects of past WFH. The estimates obtained after including previous-year WFH variables in the regressions are reported in Table 15 in the Appendix. Other explanatory variables are the same as in equation (1). Before COVID, the contemporaneous effects of WFH are similar to those in Tables 2 and 3, although the coefficients on intermediate WFH become less significant due to multicollinearity. All WFH estimates remain insignificant in the post-COVID regressions. Thus, estimated contemporaneous effects of WFH are robust to including past values.

Past WFH experiences are insignificant in women’s regressions in both periods and for men before COVID, so that after accounting for current WFH schedules, past WFH arrangements have no meaningful effect on BMI and obesity. For workers before COVID, this implies that their body weight is expected to decrease once they transition from the intermediate WFH to 100% of time office work. Having high WFH in the previous year has a marginally significant effect on men’s likelihood of obesity before the pandemic, suggesting that men tend to gain and lose weight slower than women. There is no evidence of cumulative effects for either gender. When estimating the model with past WFH values only, the coefficients are very similar to those in Table 15 and are largely insignificant. In what follows, we use the concurrent values of WFH and body weight, which allows us to

focus on the strongest effects.

We also estimated the models with future values of WFH indicators included as additional explanatory variables. Although these regressions do not have causal interpretation, they can be used to check whether a time-specific weight gain may lead to higher probability of hybrid work in the next period. Future WFH values are individually and jointly insignificant in BMI and obesity regressions for women before COVID, which implies no feedback from the current period weight change to WFH in the following year. For women during the years after COVID, the future low WFH indicator has a significant negative effect on obesity, suggesting that in recent years women who experienced a positive shock to obesity in the current year were less likely to be in a low-intensity WFH arrangement the following year. In contrast, intermediate WFH has significant positive effects on BMI and obesity among men before COVID. This suggests that men who transitioned from fully-in-the-office to hybrid work arrangements before COVID experienced weight gain the previous year. All effects of WFH are insignificant for men in the post-COVID years. Hence, the hypothesis that weight gain leads to worker transitions into hybrid work arrangements finds some support in men’s regressions but not in women’s regressions.

Reverse causality. A common concern in studies of determinants of health is the possibility of reverse causality. In the case of WFH, one can be concerned that an individual’s weight gain or related health issue may motivate them to seek flexible work arrangements rather than the other way around. To mitigate this problem, we include a rich set of controls, as discussed in Section 4.1. Moreover reverse causality argument is inconsistent with nonlinear effects of WFH that we find. If reverse causality were present, one would expect individuals to seek even more hours of home-based work when experiencing health conditions that lead to greater weight gain. However, contrary to this expectation, we find that WFH in women and men before the pandemic is associated with more weight gain if they work 50-70% of hours at home, but not if WFH is more than

70% hours. Finally, the estimated effects of WFH on body weight outcomes are contemporaneous, as we do not find cumulative effects of WFH on the measures of body weight. There is also no indication that idiosyncratic weight gain in the current period leads to more WFH in the following year among women. For women, the positive effect of WFH is only observed at the time when this arrangement is current and the size of the effect is quite small, about 0.93 kg. It appears unlikely that such an increase in body weight would motivate women to seek changing their work arrangements and do so temporarily. The results for men are less clear-cut, as the lead values of WFH are significant in pre-COVID regressions; however, nonlinear effects and small effect sizes still suggest that reverse causality is unlikely. As documented in the literature, workers tend to favor WFH because it allows them to save time by reducing commute and provides more flexibility to achieve a better work-life balance (Lee (2023)). Although some workers likely seek WFH for health reasons, the medical conditions known to lead to weight gain are usually chronic (hypothyroidism, diabetes, depression, arthritis, heart or liver failure) and so is the corresponding weight gain. This again suggests that the modest contemporaneous effects that we find are unlikely to be caused by reverse causality.

Sample selection. To check whether selection bias is present, we implemented the procedure outlined in Section 4.1. Equation (3) was estimated using the pre-COVID and post-COVID whole samples and by gender. Results are presented in Table 16 in the Appendix. As seen in the Table, there is no evidence of selection bias, except for the post-COVID BMI regression for men, where the correction terms are jointly marginally significant ($p\text{-value} = 0.074$). Using the second and fourth order polynomials produced very similar results. As an alternative test, we included past and future values of the selection indicator in equation (1) and tested their statistical significance. The past and future values of the selection indicator were jointly insignificant in all regressions. Hence, there is very little evidence of selection bias in the BMI and obesity regressions.

Consistent with the test results, correcting for sample selection has practically no impact on the estimated coefficients of WFH variables. The estimated effects of WFH are almost identical to the uncorrected estimates, both in terms of magnitude and significance (Table 16 in the Appendix).

5 Possible Mechanisms

5.1 Physical Activity and Time Use

One potential mechanism underlying the effects of WFH on body weight outcomes is the changing frequency of physical exercise and time use. To study the relationship between WFH and exercise, we estimate the linear two-way fixed effects model (1) using frequency of physical activity as the dependent variable. The effect of WFH on time use is estimated using the fixed-effects Poisson model:

$$E(time_{it}) = \exp(\theta_t + \beta_1 lowWFH_{it} + \beta_2 intermWFH_{it} + \beta_3 highWFH_{it} + \gamma' X_{it} + c_i), \quad (4)$$

where $time_{it}$ is the number of weekly hours spent in a particular type of activity, $\exp(\cdot)$ is an exponential function, and the explanatory variables are the same as in equation (1).⁹ Similar to the fixed-effects Logit, individual effects c_i are removed by specifying the conditional likelihood function that does not depend on c_i , so that there is no need to include individual-specific indicators as covariates (Wooldridge, 2010). The effects of WFH in equation (4) are semi-elasticities, which are estimated using individual-specific changes in time use and WFH arrangements. Because identification is based on the variation across time, respondents whose time use outcomes remain constant are not contributing to the estimation. Robust standard errors are computed to account for

⁹In this context, the estimation method in the Poisson quasi-maximum likelihood estimator (Wooldridge, 2010, Chapter 18).

possible over-dispersion.

Table 6: Estimated Effects of WFH on Physical Activity

	Pre-COVID			Post-COVID		
	Whole sample (1)	Women (2)	Men (3)	Whole sample (4)	Women (5)	Men (6)
Low WFH	-0.043** (0.017)	-0.027 (0.028)	-0.053** (0.022)	-0.015 (0.042)	0.011 (0.065)	-0.039 (0.054)
Intermediate WFH	0.038 (0.075)	0.091 (0.115)	0.011 (0.096)	-0.140** (0.068)	-0.027 (0.098)	-0.209** (0.094)
High WFH	0.098 (0.065)	0.112 (0.106)	0.079 (0.082)	-0.118 (0.073)	-0.136 (0.111)	-0.077 (0.096)
Observations	64,349	24,544	39,805	15,010	6,209	8,801

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects. *** statistically significant at the 1%, ** 5%, * 10%.

The results are reported in Tables 6 and 7. As seen in Table 6, WFH is not associated with a higher frequency of physical activity. Indeed, the effects are slightly negative and significant for men with low WFH arrangements before COVID. This may happen if the WFH intensity and commute time savings are too low to offer sufficient time flexibility and opportunities to invest in health. Likewise, having intermediate WFH arrangements after COVID is associated with a lower frequency of physical activity among men, and the effect is more sizable.

Table 7: Estimated Effects of WFH on Time Use

	Pre-COVID					Post-COVID				
	Commute	Errands	House work	Outdoor tasks	Child care	Commute	Errands	House work	Outdoor tasks	Child care
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
<i>Women</i>										
Low WFH	0.034*	-0.016	-0.001	0.012	0.062	-0.046	0.035	0.115***	0.014	0.125
	(0.019)	(0.021)	(0.014)	(0.034)	(0.042)	(0.053)	(0.056)	(0.037)	(0.072)	(0.089)
Intermediate WFH	-0.299***	0.175**	-0.029	0.041	-0.069	-0.213***	0.054	0.126**	0.163	0.106
	(0.096)	(0.072)	(0.065)	(0.123)	(0.179)	(0.082)	(0.086)	(0.060)	(0.114)	(0.140)
High WFH	-0.856***	0.183***	0.140***	0.037	-0.077	-0.544***	-0.029	0.166***	0.046	0.073
	(0.152)	(0.064)	(0.054)	(0.107)	(0.122)	(0.106)	(0.081)	(0.056)	(0.124)	(0.124)
Observations	20,511	20,717	20,948	18,623	8,931	4,323	4,547	4,575	3,866	1,899
<i>Men</i>										
Low WFH	0.022*	0.005	0.036***	0.014	0.008	0.016	0.019	-0.009	0.023	0.013
	(0.012)	(0.016)	(0.013)	(0.017)	(0.022)	(0.033)	(0.043)	(0.032)	(0.058)	(0.053)
Intermediate WFH	-0.253***	0.079	-0.011	0.086	0.111	-0.132**	0.038	0.008	0.060	0.180*
	(0.072)	(0.065)	(0.045)	(0.074)	(0.099)	(0.066)	(0.079)	(0.053)	(0.079)	(0.098)
High WFH	-0.690***	0.086*	0.116***	0.058	-0.044	-0.683***	0.033	0.102*	-0.029	0.021
	(0.100)	(0.050)	(0.039)	(0.057)	(0.074)	(0.088)	(0.079)	(0.056)	(0.101)	(0.106)
Observations	34,671	34,393	34,885	34,298	20,437	6,557	6,715	6,805	6,553	3,531

Robust standard errors are in parentheses. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects. *** statistically significant at the 1%, ** 5%, * 10%.

Regarding time use, the results indicate that commute time tends to be significantly lower when working at home (columns (1) and (6) in Table 7). However, such beneficial effects are only enjoyed by workers with intermediate and high WFH. In contrast, workers with low WFH before COVID spend 2-3% more hours on the commute than employees working only in the office, and there is no difference after COVID. Note also that in Table 1, average commute hours are about 12% higher before COVID than after the pandemic. This suggests that even though there is heterogeneity in the amount of time saved due to WFH and less commute, the actual amount of freed-up time is generally lower before COVID.

It is possible that workers with limited WFH bring home tasks that they cannot complete during a regular workday because of either excessive workload or limited productivity. This appears to be the case during the pre-pandemic period. The estimates from the descriptive regressions presented in Table 8 show roughly 1% (0.4%) longer employment hours for women (men) in low WFH settings than for those working 100% in the office before COVID. Men with intermediate WFH also spend about 2.4% more hours in paid employment before COVID; however, the sign of the effect reverses after the pandemic. The absence of commute time savings and longer working hours before the pandemic help explain the negative effects of low WFH on physical activity in Table 6, columns (1) and (3).

Given the observed differences in commute and work hours, it is not surprising to see that workers with high WFH tend to devote more time to home activities than the other groups (Table 7). In the earlier period, employees with both intermediate and high WFH spend a sizable portion of the freed-up time on errands (shopping, banking, paying bills, etc.). However, only workers with high WFH dedicate more time to physically active housework activities (cooking, cleaning, washing clothes, etc.) – a roughly 15% increase for women and 12% for men. In contrast, there is less variation after the pandemic.

Table 8: Estimated Effects of WFH on Employment Hours

	Pre-COVID			Post-COVID		
	Whole sample (1)	Women (2)	Men (3)	Whole sample (4)	Women (5)	Men (6)
Low WFH	0.007*** (0.002)	0.011** (0.004)	0.004* (0.002)	-0.010 (0.007)	-0.006 (0.013)	-0.014* (0.008)
Intermediate WFH	0.027** (0.012)	0.035 (0.023)	0.024* (0.014)	-0.024** (0.011)	-0.021 (0.018)	-0.027* (0.014)
High WFH	-0.008 (0.012)	0.000 (0.024)	-0.010 (0.011)	-0.008 (0.013)	-0.023 (0.023)	0.006 (0.013)
Observations	56,153	20,899	35,254	11,419	4,565	6,854

Robust standard errors are in parentheses. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** statistically significant at the 1%, ** 5%, * 10%.

During the post-COVID period, women in all WFH groups spend on average more time on physically active housework tasks. The estimated effect on housework is the largest for high WFH (18%) and smallest for low WFH (12%). Similarly, after the pandemic men with high WFH tend to allocate more time to housework (10%), while men with intermediate WFH on average spend more time caring for children (20%).

5.2 Diet

Another possible mechanism that could explain the observed relationship between WFH and person's body weight is calorie consumption. To explore this potential mechanism we use the linear two-way fixed effects model (1). The explanatory variables are the same as in the BMI and obesity regressions, while the dependent variables measure the frequency

Table 9: Estimated Effects of WFH on Diet pre-COVID

	Baked goods (1)	Snack foods (2)	Sweets & ice-cream (3)	Bread products (4)	Hot chips (5)	Processed meat (6)
<i>Women</i>						
Low WFH	-0.081 (0.066)	0.113 (0.072)	0.010 (0.075)	0.003 (0.087)	0.097* (0.052)	0.013 (0.064)
Intermediate WFH	-0.172 (0.360)	0.152 (0.353)	0.167 (0.266)	0.693* (0.385)	0.828*** (0.224)	0.257 (0.235)
High WFH	-0.147 (0.212)	0.182 (0.328)	-0.289 (0.305)	0.086 (0.265)	-0.098 (0.208)	0.397* (0.235)
Observations	6,702	6,695	6,700	6,713	6,697	6,706
<i>Men</i>						
Low WFH	0.006 (0.053)	0.001 (0.048)	-0.007 (0.050)	0.012 (0.055)	-0.006 (0.043)	0.034 (0.047)
Intermediate WFH	0.158 (0.182)	0.141 (0.228)	0.172 (0.172)	0.358 (0.308)	0.166 (0.165)	0.047 (0.177)
High WFH	-0.212 (0.175)	-0.071 (0.171)	0.131 (0.145)	-0.333 (0.230)	-0.063 (0.141)	0.173 (0.134)
Observations	10,845	10,833	10,835	10,835	10,825	10,844

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects. *** statistically significant at the 1%, ** 5%, * 10%.

of consumption of different types of food described in Section 3. Estimation is performed for the pre-COVID period, for which diet variables are available.

The results are presented in Table 9 and show that women who WFH tend to consume several unhealthy foods more frequently. Specifically, high WFH is associated with slightly increased consumption of processed meat among women – approximately twice a week as opposed to the sample average of once a week. Moreover, women with intermediate WFH arrangements on average have one or two more intakes of hot chips (fried potatoes, french fries, hot chips or wedges) per week than women who do not WFH. The latter finding is consistent with more frequent consumption of fast food meals, but it is not possible to verify this from the data. Intermediate WFH is also positively related to the consumption of bread products by women, although the effect is only marginally significant.

These results are consistent with the earlier finding that women with intermediate WFH tend to have a higher BMI and increased likelihood of obesity before COVID. However, the insignificant effects on BMI and obesity for women with high WFH indicate that diet likely plays a minor role, especially because the association between WFH and diet is insignificant for most unhealthy foods. It appears that time spent on physically active home tasks is the likely driver in the relationship between body weight and WFH.

6 Conclusion

This paper investigates the impact of WFH arrangements on individual body weight using the longitudinal HILDA Survey data set. To obtain more reliable results, we employ panel data methods that account for individual differences in health and perform several robustness checks, including small modifications in the definitions of WFH variables and sample selection bias correction.

We find that the estimated effects of WFH are largely insignificant. Some positive

effects are found before COVID, but they are practically small and only observed for full-time workers with 50-70% hours worked at home. Exploring the underlying mechanisms reveals notable differences in time use by period. Before COVID, employees with low WHF tended to spend more time on commute, while work hours tended to be longer for employees with low and intermediate WFH arrangements. In contrast, after the pandemic WFH is associated with a significant reduction in commute and increased time dedicated to active home tasks for workers in all hybrid work arrangements. These findings indicate a changing nature of WFH between the two periods. Importantly, we find little evidence of a systematic relationship between body weight measures and WFH, particularly after the COVID-19 pandemic.

As mentioned earlier, establishing causal relationships using observational data is challenging due to possible confounding factors. Findings of nonlinear effects that are contemporaneous and limited in magnitude suggest that reverse causality is not a likely cause of the relationships found in our study and give us more confidence in our results. Of course, they do not guarantee that our results are completely bias free. Future research can explore a possibility of conducting a randomized control trial on this topic to obtain additional evidence.

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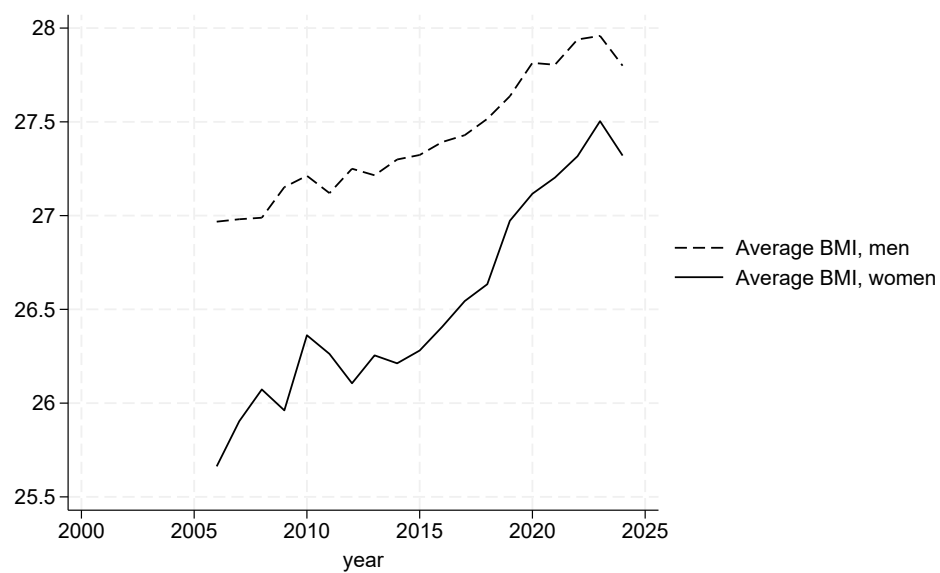
A Appendix

Table 10: Sample Construction (Waves 6-19, 22-24, Full-Time Workers)

	Number of observations	Percent (%)
Initial sample	455,082	100.00%
<i>Reasons for dropping observations</i>		
Age is less than 18 or greater than 64	177,190	38.94%
Does not work	78,562	17.26%
BMI is missing	59,839	13.15%
BMI is less than 17	558	0.12%
BMI is greater than 45	1,289	0.28%
Full-time student	8,327	1.83%
Self-employed	11,677	2.57%
Working but not paid	66	0.01%
Weekly work hours < 35 (part-time worker)	32,791	7.21%
Weekly work hours > 70	1,042	0.23%
Holds multiple jobs	3,525	0.77%
Occupation information is missing	51	0.01%
Agricultural worker	152	0.03%
Hours worked from home are missing	2	0.00%
Education information is missing	73	0.02%
Pregnancy information is missing	17	0.00%
Recent injury/disease information is missing	399	0.09%
Job change information is missing	34	0.01%
Final sample	79,488	17.47%

Note: Observations were dropped sequentially for listed reasons.

Figure 2: Average BMI, Full-Time Workers, by Gender.



Note: Averages are computed for full-time workers satisfying sample restrictions described in Section 3.

Table 11: Estimated Effects of WFH on BMI and Obesity, Exclude Pregnant Women.

	Pre-COVID		Post-COVID	
	BMI	Obese	BMI	Obese
	(1)	(2)	(3)	(4)
<i>Whole sample</i>				
Low WFH	0.034 (0.028)	0.004 (0.004)	0.071 (0.063)	-0.003 (0.009)
Intermediate WFH	0.249** (0.117)	0.036* (0.019)	0.055 (0.102)	0.001 (0.015)
High WFH	0.067 (0.093)	0.017 (0.014)	0.122 (0.113)	0.005 (0.018)
Observations	63,181	63,181	14,609	14,609
<i>Women</i>				
Low WFH	-0.027 (0.051)	-0.001 (0.006)	0.103 (0.122)	0.006 (0.012)
Intermediate WFH	0.290 (0.214)	0.100*** (0.036)	0.072 (0.184)	-0.010 (0.021)
High WFH	0.061 (0.168)	0.016 (0.019)	0.222 (0.193)	0.020 (0.025)
Observations	23,296	23,296	5,805	5,805
<i>Men</i>				
Low WFH	0.067** (0.033)	0.007 (0.005)	0.064 (0.068)	-0.007 (0.013)
Intermediate WFH	0.232* (0.139)	0.006 (0.021)	0.033 (0.116)	0.012 (0.021)
High WFH	0.078 (0.111)	0.019 (0.019)	0.032 (0.136)	-0.012 (0.026)
Observations	39,885	39,885	8,804	8,804

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** statistically significant at the 1%, ** 5%, * 10%.

Table 12: Estimated Effects of WFH on BMI and Obesity, Exclude if Recent Injury.

	Pre-COVID		Post-COVID	
	BMI	Obese	BMI	Obese
	(1)	(2)	(3)	(4)
<i>Whole sample</i>				
Low WFH	0.033 (0.029)	0.005 (0.004)	0.096 (0.064)	0.001 (0.009)
Intermediate WFH	0.295** (0.116)	0.050** (0.020)	0.006 (0.103)	0.008 (0.014)
High WFH	0.092 (0.094)	0.016 (0.015)	0.098 (0.118)	0.014 (0.018)
Observations	60,418	60,418	14,088	14,088
<i>Women</i>				
Low WFH	-0.028 (0.051)	0.002 (0.006)	0.077 (0.124)	0.009 (0.012)
Intermediate WFH	0.290 (0.203)	0.116*** (0.036)	-0.111 (0.185)	-0.008 (0.022)
High WFH	0.139 (0.164)	0.016 (0.020)	0.171 (0.201)	0.036 (0.026)
Observations	23,137	23,137	5,843	5,843
<i>Men</i>				
Low WFH	0.071** (0.034)	0.007 (0.005)	0.125* (0.068)	-0.003 (0.013)
Intermediate WFH	0.296** (0.141)	0.016 (0.022)	0.092 (0.112)	0.021 (0.019)
High WFH	0.076 (0.113)	0.014 (0.020)	0.015 (0.138)	-0.012 (0.026)
Observations	37,281	37,281	8,245	8,245

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** statistically significant at the 1%, ** 5%, * 10%.

Table 13: Estimated Effects of WFH on BMI and Obesity, Intermediate WFH Defined as 45-75% Hours Worked at Home.

	Pre-COVID		Post-COVID	
	BMI	Obese	BMI	Obese
	(1)	(2)	(3)	(4)
<i>Whole sample</i>				
Low WFH	0.027 (0.028)	0.004 (0.004)	0.046 (0.063)	-0.003 (0.009)
Intermediate WFH	0.194** (0.094)	0.035** (0.014)	0.023 (0.096)	0.005 (0.015)
High WFH	0.080 (0.100)	0.025* (0.015)	0.129 (0.115)	0.012 (0.019)
Observations	64,469	64,469	15,019	15,019
<i>Women</i>				
Low WFH	-0.037 (0.050)	0.000 (0.006)	0.024 (0.119)	0.007 (0.011)
Intermediate WFH	0.341** (0.166)	0.064*** (0.024)	0.099 (0.168)	0.004 (0.020)
High WFH	0.029 (0.173)	0.023 (0.020)	0.248 (0.188)	0.029 (0.025)
Observations	24,584	24,584	6,215	6,215
<i>Men</i>				
Low WFH	0.067** (0.033)	0.007 (0.005)	0.071 (0.068)	-0.007 (0.013)
Intermediate WFH	0.097 (0.113)	0.017 (0.017)	-0.041 (0.111)	0.011 (0.021)
High WFH	0.110 (0.123)	0.025 (0.020)	0.009 (0.143)	-0.009 (0.027)
Observations	39,885	39,885	8,804	8,804

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** significant at 1%, ** 5%, * 10%. 43

Table 14: Estimated Effects of WFH on BMI and Obesity by Gender, Intermediate WFH Defined as 55-65% Hours Worked at Home.

	Pre-COVID		Post-COVID	
	BMI	Obese	BMI	Obese
	(1)	(2)	(3)	(4)
<i>Whole sample</i>				
Low WFH	0.029 (0.028)	0.005 (0.004)	0.046 (0.062)	-0.002 (0.009)
Intermediate WFH	0.285** (0.134)	0.052** (0.025)	-0.053 (0.107)	0.005 (0.014)
High WFH	0.087 (0.095)	0.021 (0.014)	0.135 (0.107)	0.008 (0.017)
Observations	64,469	64,469	15,019	15,019
<i>Women</i>				
Low WFH	-0.036 (0.050)	0.000 (0.006)	0.033 (0.118)	0.007 (0.011)
Intermediate WFH	0.357 (0.254)	0.143*** (0.043)	0.017 (0.188)	0.014 (0.021)
High WFH	0.158 (0.174)	0.027 (0.020)	0.171 (0.183)	0.024 (0.024)
Observations	24,584	24,584	6,215	6,215
<i>Men</i>				
Low WFH	0.068** (0.033)	0.007 (0.005)	0.066 (0.068)	-0.006 (0.013)
Intermediate WFH	0.257 (0.157)	0.013 (0.029)	-0.114 (0.119)	0.003 (0.019)
High WFH	0.053 (0.110)	0.017 (0.019)	0.079 (0.124)	-0.011 (0.022)
Observations	39,885	39,885	8,804	8,804

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** significant at 1%, ** 5%, * 10%. 44

Table 15: Estimated Effects of Past WFH on BMI and Obesity

	Whole sample		Women		Men	
	BMI	Obese	BMI	Obese	BMI	Obese
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Pre-COVID</i>						
Low WFH	0.036 (0.029)	0.006 (0.004)	-0.030 (0.054)	0.003 (0.006)	0.075** (0.034)	0.008 (0.005)
Intermediate WFH	0.236* (0.121)	0.040** (0.019)	0.245 (0.216)	0.102*** (0.037)	0.222 (0.146)	0.007 (0.022)
High WFH	0.047 (0.092)	0.018 (0.014)	0.039 (0.162)	0.016 (0.020)	0.066 (0.111)	0.018 (0.018)
Low WFH in t-1	0.033 (0.028)	0.005 (0.004)	0.019 (0.051)	0.005 (0.006)	0.039 (0.033)	0.004 (0.005)
Intermediate WFH in t-1	0.094 (0.120)	-0.005 (0.018)	0.085 (0.203)	-0.013 (0.032)	0.115 (0.144)	-0.001 (0.021)
High WFH in t-1	0.050 (0.096)	0.020 (0.013)	-0.156 (0.170)	0.007 (0.023)	0.173 (0.113)	0.028* (0.016)
Observations	58,006	58,006	21,946	21,946	36,060	36,060
<i>Post-COVID</i>						
Low WFH	0.079 (0.065)	-0.002 (0.009)	0.107 (0.123)	0.009 (0.011)	0.068 (0.072)	-0.007 (0.014)
Intermediate WFH	0.007 (0.114)	0.007 (0.017)	-0.049 (0.198)	-0.007 (0.022)	0.066 (0.127)	0.023 (0.024)
High WFH	0.100 (0.121)	0.010 (0.019)	0.164 (0.205)	0.025 (0.027)	0.050 (0.141)	-0.006 (0.027)
Low WFH in t-1	0.001 (0.062)	0.005 (0.009)	-0.036 (0.108)	-0.000 (0.012)	0.000 (0.073)	0.007 (0.012)
Intermediate WFH in t-1	-0.118 (0.111)	0.008 (0.016)	-0.281 (0.171)	-0.005 (0.024)	0.048 (0.140)	0.024 (0.020)
High WFH in t-1	0.006 (0.083)	0.003 (0.012)	-0.079 (0.140)	-0.012 (0.016)	0.053 (0.097)	0.013 (0.016)
Observations	13,532	13,532	5,583	5,583	7,949	7,949

Standard errors are adjusted for clustering at the individual level. All regressions include age indicators, highest grade of secondary education completed, indicators for completed secondary education and post-secondary degrees, an indicator for respondent reporting a serious personal injury or illness during the last 12 months, pregnancy indicators, real per capita household income, presence of a long-term health condition, whether long-term health condition limits work, marital status, occupation, wave and state indicators, and account for individual-home-job fixed effects.

*** significant at 1%, ** 5%, * 10%.

Table 16: Testing and Correcting for Sample Selection in BMI and Obesity Regressions.

	Pre-COVID		Post-COVID	
	BMI (1)	Obese (2)	BMI (3)	Obese (4)
<i>Whole sample</i>				
Low WFH	-0.002 (0.027)	0.000 (0.003)	0.052 (0.059)	-0.001 (0.008)
Intermediate WFH	0.235** (0.116)	0.035** (0.018)	-0.028 (0.102)	0.001 (0.014)
High WFH	0.027 (0.089)	0.013 (0.013)	0.038 (0.114)	0.007 (0.017)
Joint significance of lambda	$F_{3,13463}=0.21$ p-val=0.8868	$F_{3,13463}=0.90$ p-val=0.4423	$F_{3,7355}=2.41$ p-val=0.0646	$F_{3,7355}=1.37$ p-val=0.2485
Observations	64,469	64,469	15,026	15,026
<i>Women</i>				
Low WFH	-0.056 (0.047)	-0.002 (0.005)	0.091 (0.107)	0.008 (0.011)
Intermediate WFH	0.401** (0.203)	0.106*** (0.033)	-0.086 (0.174)	-0.007 (0.018)
High WFH	0.007 (0.160)	0.011 (0.019)	0.080 (0.183)	0.020 (0.022)
Joint significance of lambda	$F_{3,5924}=1.06$ p-val=0.3656	$F_{3,5924}=1.24$ p-val=0.2932	$F_{3,3164}=0.70$ p-val=0.5543	$F_{3,3164}=0.83$ p-val=0.4755
Observations	24,584	24,584	6,215	6,215
<i>Men</i>				
Low WFH	0.028 (0.032)	0.001 (0.005)	0.030 (0.067)	-0.008 (0.012)
Intermediate WFH	0.149 (0.140)	-0.003 (0.020)	0.001 (0.115)	0.006 (0.020)
High WFH	0.026 (0.105)	0.013 (0.017)	-0.029 (0.138)	-0.013 (0.024)
Joint significance of lambda	$F_{3,7538}=0.33$ p-val=0.8018	$F_{3,7538}=0.35$ p-val=0.7903	$F_{3,4190}=2.31$ p-val=0.0744	$F_{3,4190}=0.39$ p-val=0.7604
Observations	39,885	39,885	8,811	8,811

Standard errors are adjusted for clustering at the individual level. Controls are the same as in Tables 2 and 3. *** statistically significant at the 1%, ** 5%, * 10%.